

Demand for electric power in Norway

Estimating Price and Substitution Elasticities

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Summary

The main goal of this master thesis is to estimate how the prices of electricity and heating oil affect the aggregate demand for electric power in Norway. The sample period is 2000-2010. I find that aggregate demand is responding to prices. But the effect is limited. The thesis finds that the price elasticity during the summer becomes stronger and more significant if one control for a structural break in late 2004. This indicates that the mandatory setup of automatic hourly consumption reporting systems have influenced electricity demand. The results also improves in quality if one correct for the months of the greatest economic turmoil during the financial crisis of 2008-09.

Compared to existing studies the thesis makes use of more recent data and it takes longer time periods into account. I estimate my models over a much longer sample period than have been usual. My models also control for more explanatory variables than the existing studies (I am aware of). For example, earlier studies do not bring the price of heating oil into their models. As heating oil is a substitute to electrical heating, these studies may suffer from omitted variables bias. By controlling for more variables, my models may be more reliable in describing electric power demand. The longer sample period also makes it possible to extract longer term effects and to model market dynamics in greater detail.

Information about consumer behavior in the period may be useful for future investment decisions in infrastructure and production capacity. Accurate information about price and substitution elasticities may also be of interest for improving climate policies and tax regimes. In the next two sections I present my methods and the main results of the thesis.

Methods

I estimate a demand equation for electricity combining instrumental variable regression methods and autoregressive distributed lag models. To identify strong instruments, important explanatory variables and relevant market dynamics, I use the automatic model selection software implemented in OxMetrics 12. The software is further used for identifying large outliers, split sample analysis, forecast tests and in estimating the steady state solution to the model. The dataset and code is available for other researchers upon request.

A central decision to make in a study of the Norwegian market for electricity is the choice and measurement of an electricity price variable. In the deregulated market after 1991, producers and consumers were free to establish bilateral contracts and several contract types (and prices) therefore exist. The price can also vary between different regions within the country. Some consumers therefore follow long term fixed price contracts while others buy in the Nord Pool spot market. Standard variable price contracts are also common. In these contracts, the supplier must notify price hikes two weeks in advance. I argue that the standard variable price contract is the best contract for my purposes. The main arguments are that: i) the prices in the different contracts tend to follow each other. ii) the price is the same across all regions if one use this variable.

To identify valid instruments for the price of electricity, broad and accurate information about the market is necessary. A section describing key statistics of the Nord Pool area is therefore an important part of the thesis. I use three different variables as instruments: Inflows, reservoir contents and the price of coal. Inflows to hydropower reservoirs are probably not affecting electricity demand directly. Reservoir content levels will affect the present value of the water reservoirs and thus the behavior of hydropower producers. Furthermore, coal is barely used for other purposes than electricity production. In the thesis I argue that different transformed versions of these variables only affects the supply side of the market, and that they therefore could be used as instruments for the price of electricity. The instruments are thus useful for the identification of supply and demand side effects.

Accurate information about the market is also important for categorizing exogenous explanatory variables correctly. In Norway, electricity is much used for heating during the long and cold Norwegian winter. The winter

season is also dark and electricity is therefore also used for lighting. This supports the inclusion of a variable related to temperature, as well as seasonal controls that capture the changing lighting conditions. As electricity is mostly used for technical equipment during the summer season, one may also expect that the price elasticity is different during the summer. I therefore include a term to adjust for this potential seasonal effect. During national holidays such as Christmas and Easter, manufacturing is reduced. The model should therefore include variables capturing this. Furthermore, the income and the economic activity level also affect the demand for electricity. The gross domestic product of Norway (excl. offshore activity) is therefore included in the models.

Another potentially crucial factor for understanding the electricity market is how often consumption is reported. Prior to 2005, only units consuming more than 400,000 kWh of electricity annually were required to report their electricity consumption at hourly intervals. Systems consuming less generally reported their consumption monthly and their bill was determined according to a typical consumption pattern. Hence, only very large consumers had an incentive to adjust demand according to short time price fluctuations. In 2005, the requirement was made mandatory to systems consuming 100,000 kWh or more annually as well. Increased awareness about the possibility to taking advantage of short term price fluctuations may have caused a structural change in the market after this period. In about five years, the system is planned to be required on practically all systems. How the demand side has responded to the 100,000 kWh changes of 2005 may therefore give us useful information about how hourly reporting in all units will affect the market.

Future analysis could adjust for regional price differences in electricity prices and grid rents. One could also take the distribution of contract types into account, i.e. how many percent of the consumers that were on spot price contracts. Furthermore, one could include more explanatory variables. The price of carbon dioxide emission and natural gas are obvious candidates. But wood related heating products could also be used. Carbon dioxide emission allowances and natural gas prices data are available. But these variables are difficult to model. Good data on the price of wood related products are hard to find. Micro level data on consumption could also yield alternative to the approach I am using.

Main results

My final model estimates the long-run price elasticity at -0.1235 in the winter season. In the summer season the price elasticity is estimated at -0.0173. The seasonal difference is likely due to greater substitution availability during the winter. The final model further estimates the substitution elasticity with regards to heating oil at 0.0486. A one percent increase in the price of heating oil thus increase the demand for electricity by approximately 0.05 percent. As explained in chapter 2, the electricity price amounts to roughly one third of the total electricity cost. One could therefore approximate the total electricity price effect by multiplying the estimated price elasticities by a factor of three.

Johnsen (2001) estimates the price elasticity to be between -0.05 and -0.35. He finds the price elasticity to be the highest when price levels are high. He thus also finds the greatest price elasticities during the winter season. The fact that he finds the price elasticities to be greater than I do may have several reasons. I include several variables that he does not control for. Furthermore, he used data from the mid-1990s, and the market may have structurally changed since then. The sample length of my study is much longer than the sample period he used.

The estimated elasticities in my study are greater than those found by Bye and Hansen (2008). They estimate the long-run direct spot price elasticity to be -0.02 in the winter and generally zero (inelastic) during the summer. They look at a shorter period of time than I do, and my results may therefore capture more long term effects more accurately (due to sample size). They are furthermore analyzing the spot price market, which has greater price volatility. As the actual price paid is generally based on a monthly average price, these fluctuations are not generally of practical importance for small or medium sized consumers.

My analysis does indeed find that something happened to the market in late 2004. The substitution effect became stronger and more significant. The summer price elasticity also increased. The introduction of mandatory hourly report systems is the likely reason behind this structural change. Adjusting for this as well the financial crisis, the

parameters remain stable in sub-sample tests. This suggests that the model also can be used for forecasting purposes.

The conclusion is thus that the demand side of the Norwegian electricity market responds to price movements. But the response is limited. This suggests that a tax on electricity is probably quite efficient, because consumers will not substitute consumption away from electricity to a great extent. Furthermore, the results indicate how challenging it is to reduce electricity demand significantly for, i.e., eco-political causes.

Preface

Ragnar Nymoen has supervised this master thesis. He has been very accessible throughout the work process, provided important feedback and corrected errors. I would like to express my appreciation of his efforts. Moreover, I would like to thank Kristina Remec at Nord Pool Spot AB and Susann Zimmer at the European Energy Exchange AG for giving me access to their databases. Nils-Henrik von der Fehr also provided advice in the early stages of the thesis.

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1. Introduction

Norway has traditionally had low and politically determined electricity prices. Prior to 1978 prices were political decided and based on average production costs. Investment in new production capacity was also a political matter. Although the average cost principle changed in 1978, prices and investment decisions were still politically decided until the energy act of 1991 changed these mechanisms completely. The pricing and investment decisions were marketized. Almost twenty years after this deregulation it is of interest to see how consumers now behave in the new deregulated system.

The main goal of this master thesis is to estimate how the prices of electricity and heating oil affect the aggregate demand for electric power in Norway. The sample period is 2000-2010. I find that aggregate demand is responding to prices. But the effect is limited. The thesis finds that the substitution effect becomes stronger and more significant if one control for a structural break in late 2004. This indicates that the mandatory setup of automatic hourly consumption reporting systems have influenced electricity demand. The results also improves in quality if one correct for the months of the greatest economic turmoil during the financial crisis of 2008-09.

Information about consumer behavior in the period may be useful for future investment decisions in infrastructure and production capacity. Accurate information about price and substitution elasticities may also be of interest for improving climate policies and tax regimes.

Compared to existing studies the thesis makes use of more recent data and it takes longer time periods into account. I estimate my models over a much longer sample period than have been usual. My models also control for more explanatory variables than the existing studies (I am aware of). For example, earlier studies do not bring the price of heating oil into their models. As heating oil is a substitute to electrical heating, these studies may suffer from omitted variables bias. By controlling for more variables, my models may be more reliable in describing electric power demand. The longer sample period also makes it possible to extract longer term effects and to model market dynamics in greater detail.

A central decision to make in a study of the Norwegian market for electricity is the choice and measurement of an electricity price variable. In the deregulated market after 1991, producers and consumers were free to establish bilateral contracts and several contract types (and prices) therefore exist. The price can also vary between different regions within the country. Some consumers therefore follow long term fixed price contracts while others buy in the Nord Pool spot market. Standard variable price contracts are also common. In these contracts, the supplier must notify price hikes two weeks in advance. I argue that the standard variable price contract is the best contract for my purposes. The main arguments are that: i) the prices in the different contracts tend to follow each other. ii) the price is the same across all regions if one use this variable.

Another potentially crucial factor for understanding the electricity market is how often consumption is reported. Prior to 2005, only units consuming more than 400,000 kWh of electricity annually were required to report their electricity consumption at hourly intervals. Systems consuming less generally reported their consumption monthly and their bill was determined according to a typical consumption pattern. Hence, only very large consumers had an incentive to adjust demand according to short time price fluctuations. In 2005, the requirement was made mandatory to systems consuming 100,000 kWh or more annually as well. One could therefore expect a structural change in the market after this period. In about five years, the system is planned required on practically all systems. How the demand side has responded to the 100,000 kWh changes of 2005 may therefore give us useful information about how hourly measuring in all units will affect the market.

The final model estimates the long-run price elasticity at -0.1235 in the winter season and -0.0173 during the summer. Because the electricity price amounts to about one third of the total electricity cost per kWh, one can multiply these numbers by a factor of three to get an approximate of the total effects. The seasonal differences are likely due to greater substitution possibilities during the winter. One could i.e. use heating oil instead of

electricity powered ovens for heating services. The final model further estimates the substitution elasticity with regards to heating oil to 0.0486. A one percent increase in the price of heating oil thus increase the demand for electricity by approximately 0.05 percent.

The thesis also finds evidence for a structural change in the market after 2005. This may be caused by increased focus on monitoring consumption over the short term. The results further improve in quality when taking the financial into account.

Further analysis could adjust for regional price differences in electricity prices and grid rents. It could then be possible to correct for time and entity fixed effects. One could also take the distribution of contract types into account, i.e. how many percent of the consumers that were on spot price contracts. Furthermore, one could include more explanatory variables. The price of carbon dioxide emission and natural gas are obvious candidates. Wood related heating products could also be of interest. Carbon dioxide emission allowances and natural gas prices are difficult to model due to simultaneous causality. Price data on wood related products of reasonable quality are hard to find, but easy to model. Micro level data on consumption could also yield an interesting alternative to the approach of this thesis.

The paper is structured as follows: I first describe the Norwegian market for electricity. I review certain statistics of electricity consumption and production, the price of electricity and relevant substitutes, as well as relevant studies of the subject. We explain how the deregulation of 1991 and the Nordic power exchange Nord Pool changed the market. Important factors influencing supply and demand are also discussed. Since the Nord Pool markets are integrated through power cables, the supply sides in Norway's neighboring countries are also described. The econometric specifications and estimation framework is also presented.

I then build a model for aggregate electricity consumption. I estimate a demand equation for electricity combining instrumental variable regression methods and autoregressive distributed lag models. To identify strong instruments, important explanatory variables and relevant market dynamics, I use the automatic model selection software implemented in OxMetrics 12. The software is further used for identifying large outliers, split sample analysis, forecast tests and in estimating the steady state solution of the model. The dataset and batch code used is annexed.

Lastly I discuss the results. Key questions discussed are: Do my results differ greatly from results in other studies? Are there important omitted variables that can lead to inconsistent estimates?

2. The Norwegian Electricity Market

To understand the Norwegian market for electricity we have to know its structure and how it is organized. The transition from direct political influence to a deregulated regime where the authority's main responsibility is to determine the rules of the game is here essential. Furthermore, an interconnected deregulated market in Scandinavia has implications for the demand and supply side in the country. This section will first cover the basic history of price determination and investment decisions in new production capacity in Norway. Then the deregulation of 1991 and the new market based pricing mechanism will be explained. Lastly, central characteristics of the demand and supply side are presented. This information lays the basic premises for the later econometric analysis of the consumption sensitivity of electricity in Norway.

2.1. Price determination prior to deregulation

The Norwegian electricity market was for a long time, like most other electricity markets around the world, subject to heavy political regulation. Prices were prior to 1978/79 set by political institutions at various levels. The prices were to reflect the average cost of production. Since the production costs in the hydro power industry were low, the price level of electricity was also low. The supply side in most regions was dominated by a few regional producers. In 1978/79 the average cost principle was replaced: Prices were still to be set by government

institutions, but the prices were to follow the cost of building new capacity. In the ten years period after 1978 the real price of electricity increased about 3 percent annually. Electricity for a relatively large energy intensive manufacturing industry was given long term contracts at favorable prices however. More information about these contracts will be given in section 2.4.2.

During the 1980s several studies called attention to the inefficiencies the current system caused (see Bye and Strøm (2008) for a brief summary of these studies). The main objective of the deregulation of 1991 was to prevent these inefficiencies and to manage Norway's electrical resources better.

2.2. The deregulation of 1991

The deregulation of 1991 changed the market radically. The authorities' changed focus. Their main objective was now to create an efficient market for electricity. Competition was enforced and prices were to be determined on an exchange or through bilateral deals between participants. Government institutions were however keeping their ownership interest in electricity companies, but the different companies were to be organized as if private companies. Most neighboring countries later joined this market. This section describes important areas of the new system. I begin by describing the changes the deregulation brought by and how this relates to producers, consumers, grid owners and the role of the system operator. Trading procedures at the Nord Pool energy exchange is also described as this is essential in the electricity market. The three major pricing contracts and their representative market shares are presented as this may be important in determining consumer behavior. I argue that all the different contracts follow the spot prices at Nord Pool but that their short term volatility differs.

2.2.1. Physical trading and the international expansion

The generation and sale side were exposed to competition. All purchasers could after deregulation freely choose their supplier of electric power. A customer in the north could i.e. choose to get electricity supplied from a distributor based in the south of the country. Market actors (including traders and distributors) could freely establish bilateral contracts in a wholesale market for electricity. The specific features of a contract were to be decided by the participants. The time period of the contract could be from hours to years and both prices and/or quantities may be specified. Johnsen (2001) reports that bilateral contracts accounts for roughly 60 percent of the total power generation.

Statnett owns, develops and operates 95 percent of the Norwegian main grid. Different producers often own the grid in their local area. To encourage fair competition between producers, the deregulation forced companies to separate their production and their grid units. The grid unit was to be regulated as a natural monopoly while the producing units were organized so that they run as competing companies. The grid is to be open on equal terms to all market participants – even government owned companies. (Bye and Hope 2005) discuss the economics of this further.

The power exchange Nord Pool (then Statnett Marked AS) was created. Nord Pool organizes a physical day-ahead market, various derivatives markets as well as clearing services. The first trades in the forward market were done in 1993. In 1996 Nord Pool merged Norway and Sweden into one common power market. Over the next four years Finland and Danmark also joined. Today, Nord Pool has grown to be the largest international power exchange in the world (Gjølberg and Brattested 2009). Total power production in the Nord Pool area is now roughly 400 TWh annually. In 2005 there were about 400 participants buying or selling in one or more of Nord Pool's products.

In Norway, the national grid company Statnett is the system operator (SO). The SO has to be notified about all bilateral deals. If actual consumption or production doesn't correspond to what predicted, or there are unexpected line outages, the SO use the clearing market at Nord Pool to remove imbalances. In this market, Statnett chooses who will change their production or consumption in order to reach a balance in the market. This choice is based on price offers that physical producers and consumers have given a priori. Large producers like Statkraft may offer to increase their production by one GWh in a given region at a given cost in case necessary.

Large consumers may offer to reduce their consumption if properly compensated. Of a total turn-over of 2,686 TWh at Nord Pool in 2008, 1,071 TWh were clearing services (Gjølberg 2009).

When the electricity market is discussed in the Norwegian media, they generally discuss the day-ahead market at Nord Pool. This is a physical spot market where participants' trade power contracts for delivery at a specific hour the coming 24-hours. The timing of the trading is as follows: Nord Pool collects bids and offers. At noon, Nord Pool set the prices and volumes for the coming day. Then all possible congestions or capacity insufficiencies' are checked. If there are congestions or insufficient capacity, the market system establishes different price areas. Nord Pool's system operators (SOs) may also ask producers to increase (decrease) production or buyers to increase (decrease) demand in order to avoid congestion as described above. The volume data in my analysis will therefore be based on the total physical volume traded at Nord Pool and through bilateral deals. This is the total amount of electricity consumed in Norway. Because the electricity market always has to be in equilibrium, this number also equals the sum of production, imports and exports.

Norway had two pricing zones for most of the time during the sample period. But in periods of heavy demand, there were as many as four zones. Overall the Nordic market had a single price less than half of the time (Strozzi, Tenreiro, Noè, Rossi, Serati and Comenges 2007).

2.2.2. Discussion of the price variable

Different price contracts yield different incentives. A central concern in the analysis is therefore the choice of electricity price variable. I argue that standard variable price contract prices are the best measure of prices to my analysis. This section will present important distinctions between the different contracts and their popularity among consumers. An overview of the electricity price during the sample period is also described..

At the end of 2009, close to 60 percent of households and roughly 75 percent of the service industries were on price contracts related to the spot price in the Nord Pool day-ahead market¹. Fixed price and spot price contracts are dominating the manufacturing industry (excluding energy intensive manufacturing industries and wood processing industries), with market shares above 50 percent and 40 percent respectively. Variable standard contracts, where price hikes have to be announced two weeks prior to the actual rise were common among households (close to 40 percent) and the service industries (20 percent). In 2003, more than 80 percent of price contracts were based on the standard variable contract type. Its market share has gradually decreased as spot price contracts have gained popularity².

¹ Unless noted, all data in this section were originally reported by Statistics Norway.

² NVE (2009): "Kontraktstyper og markedsutvikling", <http://www.nve.no/no/Energistatus-2008/Marked/Sluttbrukermarkedet/Kontraktstyper-og-prisutvikling/>, accessed 12.04.2010

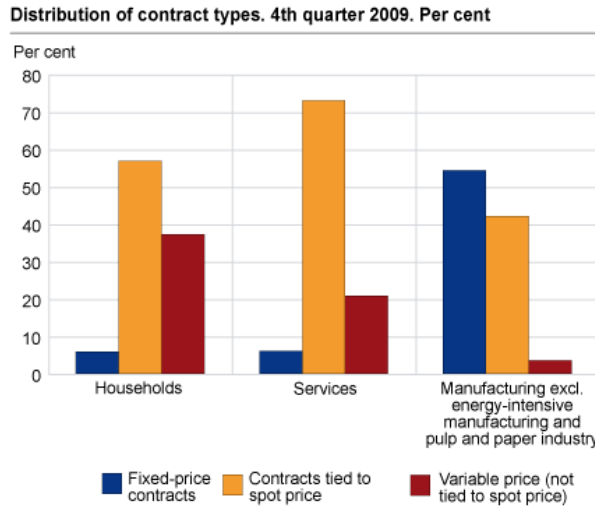


Figure 1: Distribution of contract types. Source: NVE

Standard variable price contract will be used in the analysis. There are several reasons for this. First of all I want the price variable used to be available to consumers all over the country. The spot prices often differ between pricing areas. This makes it challenging to determine the correct volume data in the different regions. Second, there is a limited practical difference between standard variable price contracts and spot price contracts. Households or businesses consuming less than 100,000 kWh annually typically report their consumption in monthly intervals. An average price is calculated according to a typical consumption pattern³. As we see in figure 2 and figure 3, the actual price paid on spot price contracts is thus not very different from the standard variable price contract prices. The lack of precise metering also creates little incentive for short term consumption adjustment. Hence, although the contract may have different prices from hour to hour, the average price and price incentives is likely to be quite similar. Large consumers of electricity are however required to have systems measuring and reporting consumption by the hour. This allows them to optimize consumption according to the day-ahead spot prices.

The latter points also limit the practical difference between fixed price contracts and contracts with variables prices. Fixed price contracts are derived from expected spot prices. The average spot price is therefore generally closer to the fixed price than the spot price on any given week, day or hour. Based on these points I conclude that the average price of standard variable contracts is a relevant measure for the electricity prices most Norwegian households and business face.

³ Called "justert innmatningsprofil" ("JIP").

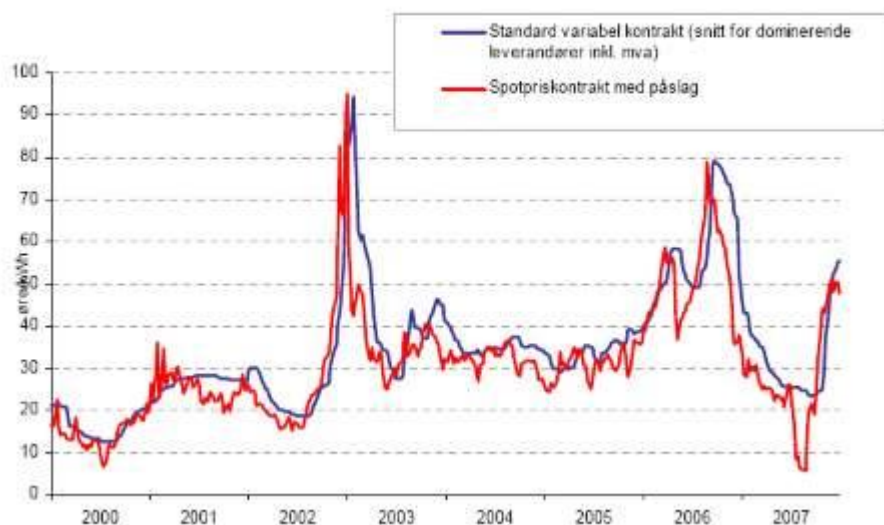


Figure 2: Standard variable contract prices (blue line) and spot price contract prices (red line) follow each other closely⁴. Source: SSB

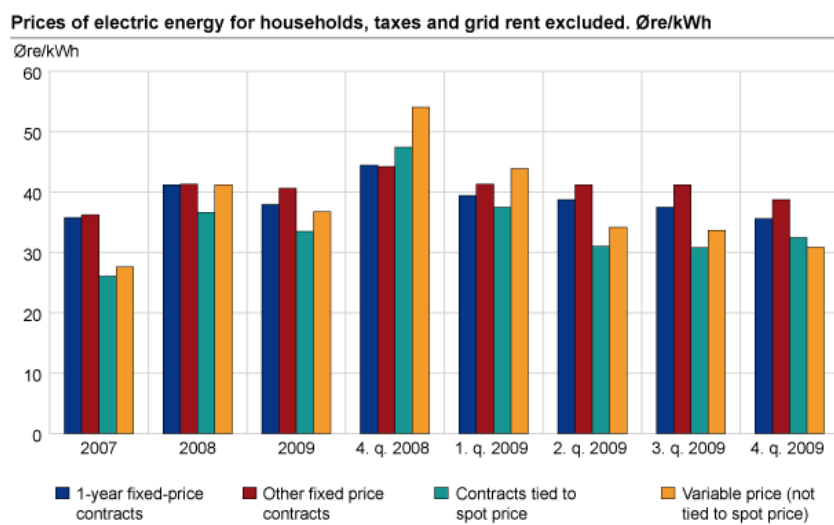


Figure 3: Prices of electricity based on contract type. Spot price contracts were generally the lowest. Source: NVE

To summarize: The deregulation therefore enforced greater flexibility for consumers and more competition to the producers of electricity. Although several pricing contracts exist, they are all quite similar or interconnected. Considering the average standard variable price contracts therefore provides a decent overview of the market prices. The next two sections will discuss the supply and demand side in the Norwegian electricity market.

2.3. Supply of electricity

In Norway, production is totally dominated by hydropower. In other Nord Pool countries the picture is more diverse. This section will describe the supply of electricity to the Norwegian market. My main focus is to identify important inputs for electricity generation, as well as whether the production capacity has changed over

⁴ NVE (2009): "Kontraktstyper og markedsutvikling", <http://www.nve.no/no/Energistatus-2008/Marked/Sluttbrukermarkedet/Kontraktstyper-og-prisutvikling/>, accessed 27.03.2010

the sample period. First the production capacity in Norway is described. Then we turn to describe the supply side of the most relevant neighboring countries. Finally, seasonality of supply is discussed.

Norway has the greatest production of hydropower per capita in the world. In a year with normal inflow the hydro production can cover 99 percent of the total electricity production in the country. The country also has wind and thermal plants, although to a very limited extent. The Ministry of Petroleum and Energy estimates total production from the Norwegian electrical system to 121 TWh in a normal year⁵.

Since the deregulation total production capacity in Norway has remained relatively stable. In a survey Strøm and Bye (2008) argue that the heavy regulation of the Norwegian electricity market caused over-investment in production capacity. Combined with higher costs of building new capacity, new investments did not meet the required rate of return under the new deregulated equilibrium prices. From 1970 to 1985 the total capacity increased by 10,730 MW, or by 4.1 percent annually. In the period from 1993 to 2005 the capacity grew by only 800 MW, and this was mainly from increased efficiency in existing generating stations.

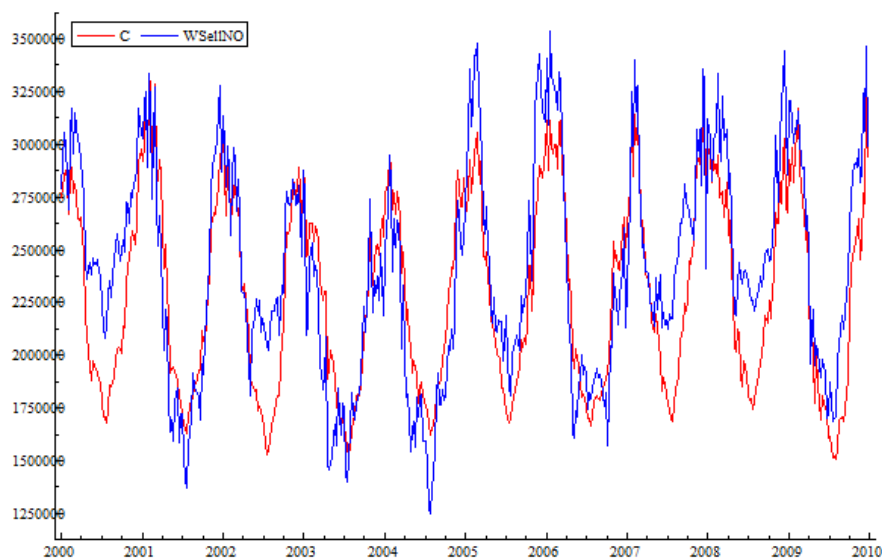


Figure 4: Production (WSellNO) vs consumption (C) in Norway from 2000-2010. Net export depends on price differences and available transmission capacity within the Nord Pool area. Unit: MWh

The supply side has also remained relatively constant in Sweden over the period. Ten nuclear power plants provide almost fifty percent of the generated electricity and there is a large proportion of hydropower. Sweden's electricity generation is almost independent of coal and oil⁶. In Denmark however, coal is the major input in electricity production with a share of 46 percent in 2004. Natural gas and renewables follow with increasing shares⁷. According to Nord Pool, hydro power, nuclear power, coal and natural gas accounted for 89,1 percent of the total production of 397,5 TWh in Finland, Denmark, Norway and Sweden in 2008 (see table 0 below).

⁵ Norwegian Ministry of Petroleum and Energy (2010): "Electricity generation", <http://www.regjeringen.no/en/dep/oed/Subject/Energy-in-Norway/Electricity-generation.html?id=440487>, accessed 23.02.2010.

⁶ European Commission (2007): "Sweden – Energy Mix Fact Sheet", http://ec.europa.eu/energy/energy_policy/doc/factsheets/mix/mix_se_en.pdf, accessed 25.02.2010

⁷ European Commission (2007): "Denmark – Energy Mix Fact sheet", http://ec.europa.eu/energy/energy_policy/doc/factsheets/mix/mix_dk_en.pdf, accessed 25.02.2010

Table 0: Electricity production in TWh from varying energy sources in the Nordic Area during 2008⁸

Energy source	Denmark	Finland	Norway	Sweden	Sum	Share (%)
Wind power	7,0	0,3	0,9	2,0	10,2	2,6%
Other	0,0			1,0	1,0	0,3 %
Biofuel	1,9	8,7	0,0	9,6	20,2	5,1 %
Waste	1,7	0,6	0,7	1,4	4,4	1,1 %
Peat	0,0	5,8		0,1	5,9	1,5 %
Natural gas 1)	7,0	11,0	0,4	1,1	19,5	4,9 %
Oil	0,9	0,3		0,6	1,8	0,5 %
Coal	16,1	8,5		0,6	25,2	6,3 %
Nuclear power		22,0		61,3	83,3	21,0 %
Hydro power	0,03	16,9	140,7	68,4	226,0	56,9 %
Total production	34,6	77,8	142,7	146,1	397,5	100 %

1) DK West includes refinery gas

A large part of Denmark's power generation comes from wind mills. At the moment this production covers about 20 percent of the country's annual electricity production. In the Nordic countries combined, however, wind power only had a limited market share of 2.6 percent in 2008. The production is volatile and depending on weather conditions. The market share on any given day may therefore be significantly higher however.

There are seasonal effects on the supply side. Some thermal plants shut down in the summer months. Snow melting and rainfall creates high inflow in the spring and over the summer. The inflow is minor in the winter due to temperatures below the freezing point. The reservoir capacity allows producers to transfer water from the high inflow periods to the low inflow periods. In the sample period the reservoir capacity was approximately 82,000 GWh in Norway, 34,000 GWh in Sweden and 5,500 GWh in Finland. The reservoir capacity remained stable over the sample period.

The supply of energy in Norway is therefore dominated by hydropower. But import and export of electricity makes other technologies important in Norway as well. The price of coal and natural gas, as well as grid outages, etc. in other countries may therefore cause shocks on the Norwegian supply side. Production capacity and technologies in use have however remained relatively stable since 2000.

2.4. Demand for electricity

This section will describe Norwegian residential and industrial energy demand. Several energy sources will be considered because these may be substitutes to electricity. I will discuss main sources for energy, seasonality and to some extent the how this has changed over the last ten years. Residential and industrial demand is treated separately.. I begin with residential demand which has decreased in per household terms over the last ten years.

2.4.1. Residential demand

More than 70 percent of the Norwegian residential energy consumption is electricity (Nesbakken 1999). But

⁸ Nord Pool Spot AS (2009): "Production split 2008", http://nordpoolspot.com/reports/Production_split/, accessed 02.03.2010

there are substitution possibilities. For example, the input share of electricity in district heating plants varies (see figure 5). This section reviews the energy from Norwegian households over the sample period. The most important energy sources are described. Flexibility between sources and seasonality is also discussed.

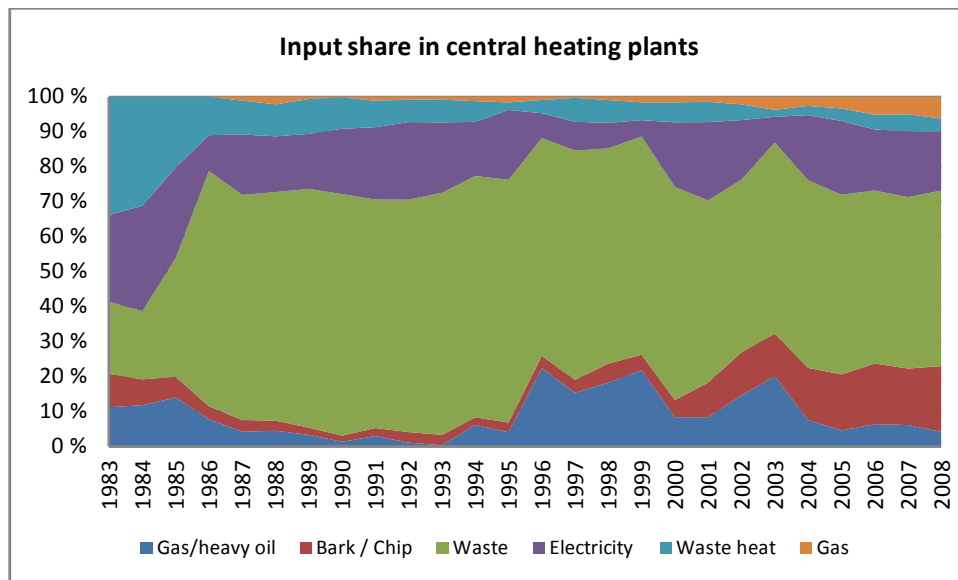


Figure 5: Input consumption as share of total consumption in Norwegian central heating plants in the period 1983-2008.
Source: Statistics Norway

Statistics Norway keeps detailed account of information regarding residential energy consumption in Norway. Norwegian households are becoming more efficient in terms of utilizing energy. The average consumption of electricity per household was 16,252 kWh in 2008⁹. This is down from 18,290 in 2001. Heating oil and paraffin consumption amounted to 1,588 kWh. This less than half of the consumption level of 2001. One should note that the prices of petroleum products were historically high in 2008. Statistics Norway emphasizes higher prices, better insulation, as well as increased focus on energy saving and efficiency, better insulation, when analyzing the major forces behind these reductions¹⁰.

Heating consumption based on wood and central heating plants remained relatively stable over the period. In 2008 wood accounted for 6,875 kWh and 718 kWh. Over the period, the number of households increased from 1,961,548 to 2,123,585. The total residential demand thus increased roughly 330 GWh from 2001 to 2008. The coal and coke consumption in 2008 was estimated to 167 GWh. This is only about one percent of the total electricity consumption. Natural gas consumption was only estimated to 36 GWh the same year. Hence, the demand for coal, coke and natural gas are relatively insignificant compared to the average residential electricity consumption.

Residential electricity consumption shows patterns of seasonality. Electricity consumption is roughly doubled in the relatively dark and cold Norwegian winter as electricity is used for heating and lighting. Air conditioners are only to a limited degree used in the Nordic countries. Flexibility is greater in the winter since most buildings have several types of heating technologies (wood, fuels, etc.).

The residential demand for electricity is therefore likely to be affected by prices for substitutes such as natural gas, heating oil and wood. The demand is also likely to show signs of seasonality since flexibility is greater in cold months. My model should take this into account.

⁹ Statistics Norway (2009): "Energiforbruk i husholdninger. 1990-2008", <http://www.ssb.no/energiregn/tab-2009-12-01-20.html>, accessed 01.03.2010.

¹⁰ Statistics Norway (2007): "Energiforbruk per husholdning, 2006", <http://www.ssb.no/husenergi/>, accessed 01.03.2010.

To summarize: Residential energy demand is dominated by electricity. Coal is close to insignificant while heating oil and wood play an important role. Natural gas has also increased its importance the later years. There are also seasonal effects of residential demand, mostly related to seasonal differences in temperature and light levels.

2.4.2. Industrial demand

Industrial demand also plays an important role on the demand for electricity. This section will describe Norwegian industrial energy demand. Industrial demand is here defined as demand from the manufacturing and mining sectors. How electricity and relevant substitutes demand have developed over the period will be the main focus. Some energy intensive firms were also given favorable long term electricity contracts in earlier periods and the implications of this are also discussed. Lastly, the impacts of national holidays are discussed.

Total energy demand from the Norwegian manufacturing and mining sectors amounted to 80,082 GWh in 2008¹¹. With a total consumption of 50,396 GWh, electricity was by far the most important product. Other important products were 2,842 GWh heating oil, 4,675 Gas (propan and butan 2,005 GWh, LNG 731 GWh and natural gas 889). The total consumption of coal was 1,007 GWh¹². Since 2000, the total energy demand from the industrial sector has decreased marginally although the real production has increased by 27 percent.

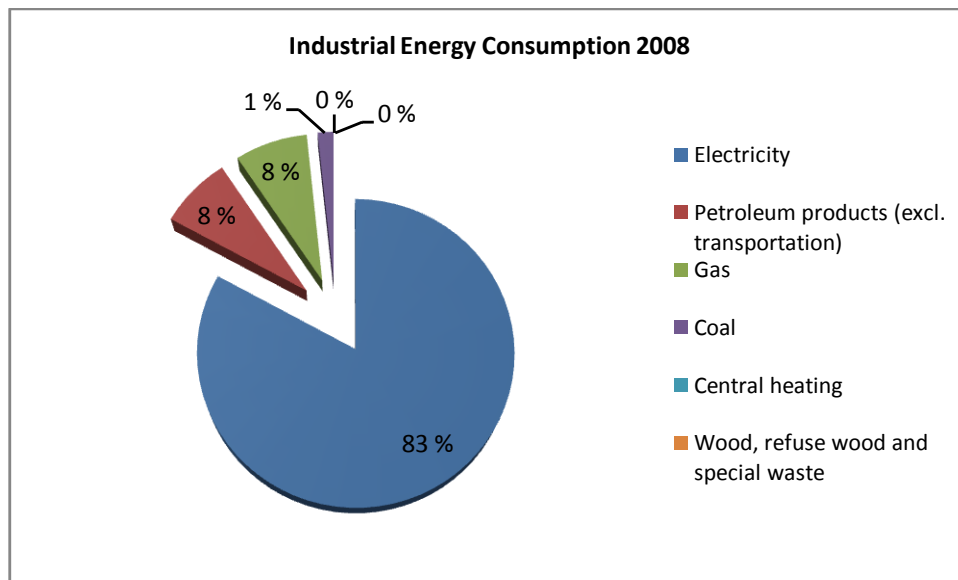


Figure 6: Total energy consumption composition by the Norwegian industrial sector in 2008 (preliminary numbers).

Norway has historically had a relatively large, energy intensive, manufacturing sector exporting metals, chemicals and pulp and paper. The new pricing principle introduced in 1978/79 did not include this sector: The sector was rather offered long term, politically determined, contracts for electricity through Statkraft. While the overall electricity price increased 11 percent nominally from 1978 to 1988, the contracts for the energy intensive manufacturing sector were close to constant (Bye and Strøm 2008). Gradually the contracts therefore became more lucrative. The contracts were not terminated after the energy act of 1991. They were however to be removed gradually as they expired. We now see that this is happening. The average nominal electricity price per GWh for energy intensive industry on average doubled from 1998-2007¹³. According to Statistics Norway this is mainly due to the repeal of lucrative contracts for electricity as well as higher electricity prices in general. Some

¹¹ Statistics Norway (2009): "Energibruk for bedrifter i industri og bergverk", <http://www.ssb.no/indenergi/tab-2009-09-08-01.html>, accessed 04.03.2010.

¹² Excl coal and coke used as reducing agent in the production process.

¹³ Statistics Norway (2009): "Industriens energibruk. Foreløpige tall 2008", <http://www.ssb.no/indenergi/>, accessed 04.03.2010.

energy intensive firms have also shut down in the period. The last subsidized contracts will terminate by 2012. If the gradual termination of contracts during the 2000s caused structural changes on the demand side, this can cause problems to the accuracy of my results.

On January 1st 2005 hourly reporting systems of electrical consumption became mandatory for systems consuming more than 100,000 kWh annually. The previous limit was 400,000 kWh. By reporting consumption at hourly incentives to utilize price fluctuations in the day-ahead spot price occur. One may i.e. reduce cost by reducing consumption during peak hours. If reporting monthly this incentive is close to non-existent because the price is averaged out according to a typical consumption pattern. This new requirement may therefore have created structural changes in the demand for electricity.

During national holidays such as Christmas and Easter much industrial production are closed down or reduced. These weeks may have significantly lower demand for electricity than other weeks.

Industrial and residential electricity demand has similarities. Like in the residential sector, the industrial sectors' energy consumption is dominated by electricity. There are also substitution possibilities for heating in the industrial sector as we saw in the residential sector. Holidays reduce the demand for electricity in the industrial sector however. And an energy intensive sector still faces favorable electricity prices, although these are gradually reduced. In addition, general economic growth may play an important role in both residential demand (through increased income) and industrial demand (through increased activity). In the next section we will utilize what we have learned in this chapter to build a model for the aggregate demand of electricity.

3. Econometric estimation

Modeling how prices affect the demand for electric power is a complex challenge. Some variables influence the supply and demand side simultaneously and there are complex dynamics in the market. For example, the price of natural gas will influence the behavior of gas powered thermal plants in Denmark. If they reduce production, the price of electricity may increase and thus influence the optimal water allocation for Norwegian hydropower producers. But we also know that gas is a substitute for electricity used for heating. Higher prices of gas may therefore increase the demand for electricity although the price of electricity has increased. If we do not specify our model correctly, this effect may make it look like the demand for electricity increase with the electricity price. But the actual effect may be due to increased costs of substitutes and higher production costs of electricity.

Dynamics may also play an important role. Cost of adjusting production may cause gas powered thermal plants to delay their reaction to changing prices. If the price of gas is volatile they may want to see significantly higher gas prices before they reduce their production. Otherwise they may lose profits due to the cost of adjusting production. The same applies to the demand side: Would a consumer replace his electrical heating system if he expects the price of electricity to be high only the coming week? It is not unreasonable to assume people to be quite slow in adjusting their heating technologies. Due to high capital costs, replacing heating equipment is only profitable if the price level is sufficiently high over longer time periods. The effect of price changes may therefore be difficult to tract in a short term model.

This section will briefly review two existing studies on the subject. These studies are more detailed or use different approaches than I do. My model will however make use of recent data, and my sample period is a good deal longer. I also control for variables they do not take into account. That said, the underlying economic theory is however quite similar. It is therefore interesting to see how our results relate to those of others. I will then describe my dataset and explain how each variable relate to the demand and the supply side of the market for electricity. At the end of the section we specify our econometric model.

3.1. Existing studies

Several researchers have studied the Norwegian electricity markets since the deregulation of 1991. Some of the studies vary in methodology and the time periods studied differ. It is therefore interesting to compare these results and see how these variations cause different results. Nesbakken (1999) discusses reasons for the large variation of estimates of elasticities. Some models use aggregated time series data while others rely on cross-sectional micro data. The variation may also be due to different types of models. Further, the observable and unobservable characteristics of households (and industrial demand for that matter) may vary across countries. She refers to Vaage (1998), who surveys different methods of estimating demand for electricity and finds large variations in income and price elasticities among households. He suggests that more time should be spent on testing existing models on new data. I will here discuss two studies in more detail. They make use of similar methodologies, but their sample period and their choice of variables are different. I will here describe two important Norwegian studies. Bye and Hansen (2008) analyze hourly spot prices to determine short and (relatively) long run elasticities. Johnsen (2001) use weekly data from an earlier sample but are otherwise using the same method.

“How do Spot prices affect aggregate demand”, Bye and Hansen (2008)

Bye and Hansen (2008) analyze how the spot price of electricity traded at Nord Pool affect aggregate demand for electricity in Norway and Sweden in both the short- and the long-run. They use a simultaneous supply and demand model approach using data from January 1st 2000 to December 31st 2004. They find that the price elasticities are lower during nights and weekends than during days and midweeks. They estimate that the full price adjustment effect takes up to six months in Norway. The direct spot price elasticity is generally zero in the summer and -0.02 in the winter, measured as a weighted average over the week. It also takes time before the price effect fully affects the market. This is lower than what found in other studies. Bye and Hansen explains this by the short time of adjustment in their model, and that they measure elasticities on the wholesale power price, while other studies usually reports elasticities based on the purchaser price. The wholesale power price does not include transmission tariffs, administrative costs, commodity taxes and value-added taxes. My price unit is thus similar, except that my variable includes the value-added tax of 25 percent.

“Demand, generation and price in the Norwegian market for electric power”, Johnsen (2001):

Johnsen (2001) also use a simultaneous equations model of supply and demand. But his sample period is shorter and is only using Norwegian data. The sample consists of weekly data from 1994 to 1995. Data for 1996 is used for post-sample examination of the model. Like Bye and Hansen, his price equation assumes price taking producers with rational expectations. He finds that the price, temperature and day-length explain 90

percent of the observed variation in the first difference for electricity demand. The price elasticity varies with price and demand conditions. In his sample, the price elasticity varies between -0.05 and -0.35. The price elasticity increases numerically the higher the price level is.

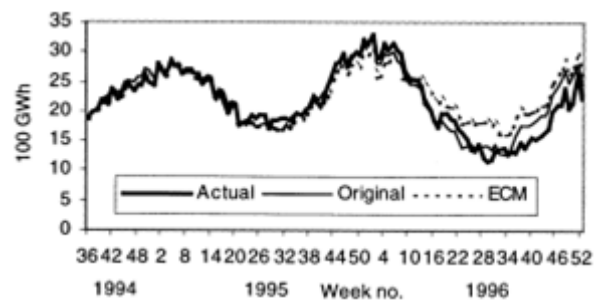


Figure 7: Actual demand vs. predicted demand by Johnsen's original and alternative (ECM) model.

Johnsen observes some very large residuals in both the price and demand equation. This suggests that the modeling of price determination is too simple, especially because these large residuals usually occur in weeks of unusual large inflow. To evaluate the model's forecasting abilities he compares it with a simple auto-regressive distributed lag model for price and demand. The main difference between the first and this second model is how price movements are modeled. In the error correcting model (ECM), electricity generation is included as an explanatory variable for the price, the coefficients are constant over the year and there are no cross-equation parameter restrictions. The new model performs generally as well as the original model within the estimation

period. The original model performs much better during the post-sample period however. During 1996, the ECM model simulates too low day-ahead prices and predicts demand to be higher. Johnsen argues that the main reason for the poor dynamic performance of the ECM alternative is the inclusion of demand as an explanatory variable in the price equation. The model thus fails to explain the high day-ahead prices during the spring and summer of 1996. Towards the end of 1996, the ECM predicts higher prices due to increased demand, and by the end of 1996 the model tracks the actual prices relatively well.

3.2. Choice of operational variables

In this section we present observable variables that may affect supply and demand. My model will take a two stage least squares perspective of the demand side. We therefore classify the potential variables into three categories, based on the description of the market from the previous section. The economic reasons for their potential influence are briefly discussed. Endogenous variables are variables that are likely to affect supply and demand simultaneously. Instrument variables are variables that only affects supply and that are uncorrelated with the demand side. Exogenous explanatory variables are control variables that only influence the demand side. All variables discussed are variables in which we have data. At the end of the section we briefly comment some other potential variables that can affect the market, but of which we don't have data.

One may include more endogenous variables than I do in this section. Natural gas prices and the price of carbon dioxide emission allowances are natural examples. In this section I will however only consider variables used in my first model. Other variables are discussed later. Note that all prices are divided by Statistics Norway's consumer price index excluding energy products (KPI-JE). The KPI-JE is interpolated from monthly to weekly levels linearly. The analysis is thus focusing on real prices.

3.2.1 Endogenous variables

The price of electricity. Naturally, the price of electricity affects both demand and supply of electricity. The dataset contains average end-prices for standard variable price contracts. I argued for the use of these prices in the section where the market was described. Value-added tax is included where eligible¹⁴. Grid rent and tax on electricity consumption is not included. Bye and Hansen (2008) assert that the spot price is approximately 1/3 of the total cost per kWh for electricity for ordinary consumers. Although their variable does not include value-added tax, this estimate more or less holds for my data (as we see in figure 8).

¹⁴ The Northern counties of Norway are exempt from the value-added tax. Note that most businesses may deduct the incoming VAT completely.

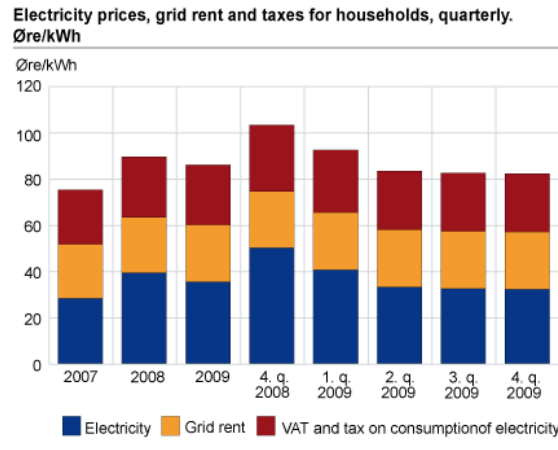


Figure 8: The electricity price is only a limited share of the total electricity cost. Generally, the electricity price is generally one third of the total electricity cost per kWh. Source: NVE

3.2.2. Instrumental variables

Instrumental variables should be correlated with the price of electricity, which we will use as an endogenous explanatory variable, but not correlated with the error term in the demand function for electricity. In a strict theoretical sense this probably holds for some of our variables. Other variables may however have a simultaneous effect on both supply and demand. This section discusses the validity of potential instrumental variables. In doing this, the detailed information about the market from chapter 2 now becomes important.

Inflow to reservoirs. Deviations from median reservoir inflow. The inflow is likely to be completely independent of demand. It is also exogenous since it is determined by nature. By looking at deviations from median inflow we correct for seasonal patterns. For Norway, the median inflow is estimated from weekly data in the period 1995-2009. For Sweden and Finland, the period is shorter (starting in 2000 and 2001, respectively).

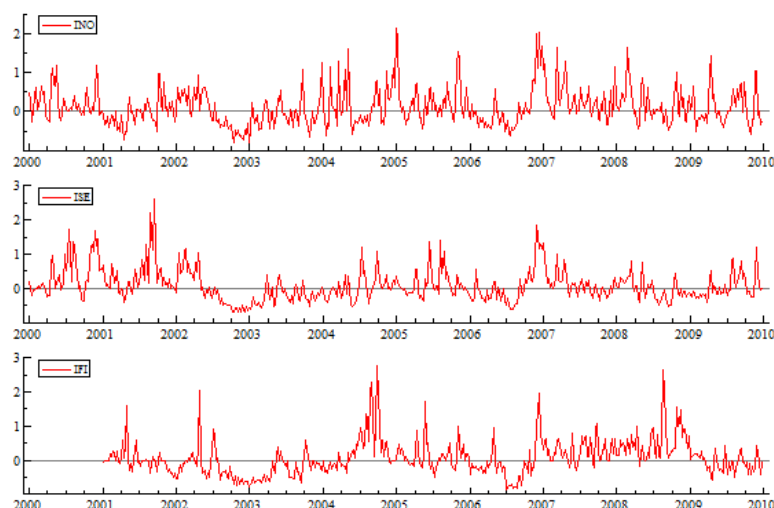


Figure 9: Deviations from median inflow in Norway, Sweden and Finland. Notice dry fall and winter of 2002-2003.

Reservoir levels. Deviations from median reservoir levels. Economists usually assume hydro producers to maximize the current value of their water reservoir. Their reservoir level may thus be endogenous and correlated with expected demand. But previous studies conclude that temperature is the major force determining demand (see i.e. Johnsen (2001), Nesbakken (1999) or Bye and Hansen (2008)) and long term weather forecasts are

inaccurate, the deviations from median reservoir levels are also likely to be exogenous. If the reservoir levels are significantly below normal, and producers historically maximized the current value of their reservoirs, one can assume producers to demand a higher price if they must empty their reservoirs further. I therefore use deviations from median reservoir levels as instruments in the econometric model. For Norway, the median is calculated using the period 1990 – 2007. The Swedish and Finnish median in the period 2000 – 2009 is used.

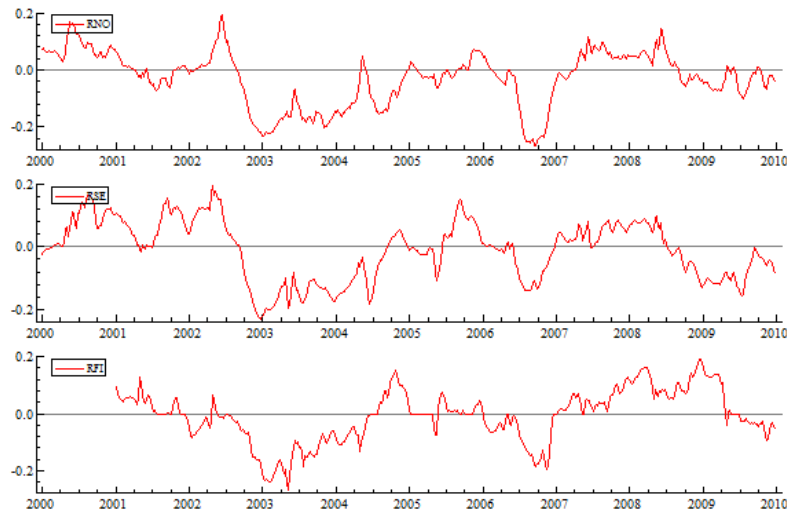


Figure 10: Deviations from median reservoir levels in Norway, Sweden and Finland. There appears to be correlation between the countries.

The price of coal. A vector of future contract prices of coal traded at the European Energy Exchange (EEX) in Germany. Coal had an input share of 21 percent of the total electricity production in the Nord Pool area in 2008. At the same time it only accounted for one percent of the industrial energy consumption in Norway. We therefore assume that the price of coal is only shifting the supply side and that the price of coal is therefore for any practical purposes a proper instrument. An increase in the price of coal will increase the marginal cost of electricity in a coal fired thermal plant, and thus the price of electricity in the Nord Pool area.

Capacity increase. Dummy for an increase of the Norwegian reservoir capacity in week 16 2004. The monitored reservoir capacity increased from 81,729 GWh to 81,888 GWh. Larger reservoirs create larger production flexibility and can influence the behavior of suppliers since the present value of the reservoirs changes. This change is likely to be uncorrelated to demand.

Summer. Due to reduced demand for heating several thermal plants are shut down in the Nordic countries in the summer (Bye and Hansen 2008). This creates a shift in supply. Summer may however be correlated to the demand for electricity, but this can be controlled for by using monthly dummies in the demand equation.

The NorNed power cable. The power cable “NORNED” opened for commercial transfer of electricity between Fedra, Norway, and the seaport of Eemshaven, the Netherlands, on May 6th 2008. Its capacity is at least 700 MW¹⁵. cable creates greater potential for export and import, and thus affects the supply side in Norway. The demand side is probably only affected indirectly through prices. I have therefore included a dummy variable for the period the cable has been in operation.

¹⁵ Tennet (2008): “NorNed cable off to a promising start”, http://www.tennet.org/english/tennet/news/veelbelovende_start_voor_nornedkabel.aspx, accessed 15.03.2010

3.2.3. Exogenous explanatory variables

Exogenous explanatory variables are variables determined outside the system. They are only directly affecting the demand for electricity. In this section I present and discuss the variables I plan to use.

Temperature. . Deviations from median temperature in five big cities – weighted by their regions share of gross national product. Electricity is to a large extent used for heating in Norway. Low outdoor temperatures increases the energy needed for a comfortable indoor temperature, and thus the demand heating services. To avoid seasonal patterns we have transformed the series to deviations from median temperature. I will test for seasonal differences in how temperature affects demand however. The median is calculated from the median weekly temperature in the period 1999-2009. The GDP weight is constant over the period and based on 2008 numbers.

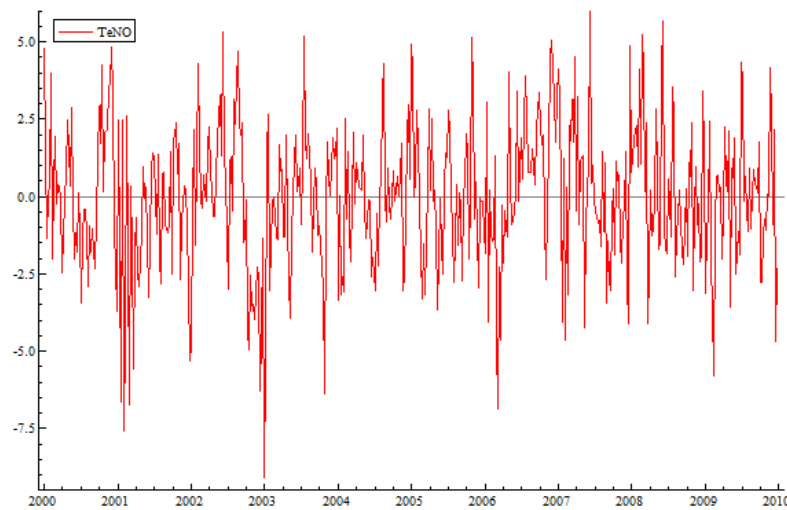


Figure 11: Deviations from median temperatures in Norway. A vector of temperatures from the biggest cities in the country weighted by their regions share of gross domestic product.

Real gross domestic product (GDP). Rising incomes and economic growth may cause increased demand for electricity. A variable for real GDP for the Norwegian mainland is therefore included. The numbers are interpolated from quarterly to weekly basis linearly. Rising electricity production and prices will cause GDP to rise, but this effect is very small compared to the size of the total level of GDP and thus negligible.

The price of heating oil. Oil accounted for only 0.5 percent of total input of the Nord Pool areas electricity production in 2008. Industrial demand for petroleum products (transportation demand excl.) amounted to 8 percent of the total energy consumption the same year. Gas/heavy oil is also a significant input in Norwegian central heating plants. A variable for heating oil, traded at the New York harbor, is therefore included in the model. It is included as a control variable because the effect on production is likely to be very limited (ref. the input shares in power generation reported in table 2)

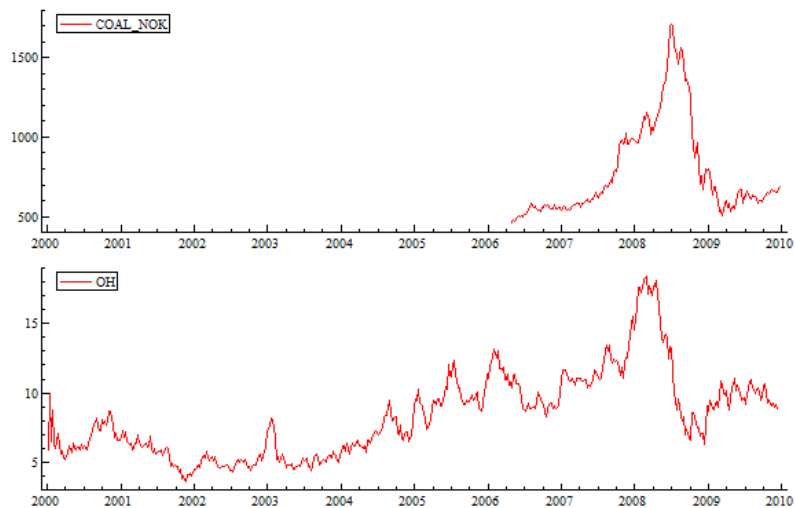


Figure 12: The price of coal and heating oil measured in NOK. Notice the large increase and decrease in the period 2007-2009.

Mandatory hourly metering and reporting systems. Stricter rules on mandatory hourly metering systems may have changed the demand function of electricity. In 2005, hourly metering became mandatory to system consuming more than 100,000 kWh of electricity. A dummy were therefore included in the dataset to control for how this potentially changed the structure of the aggregate demand function.

Christmas and Easter weeks. The national holiday of Easter and Christmas is characterized by lower industrial production and lower demand from businesses. The electricity consumption is therefore likely to fall in these periods. A dummy equal to 1 at Christmas weeks (week 52 for all years) and Easter weeks (varies between week 12 and 16 from year to year) is therefore included in our dataset.

3.3. Data

Physical electricity consumption, inflow to reservoirs, reservoir data and natural gas prices were downloaded from Nord Pool's FTP-server. Total physical electricity production is the total amount consumed in Norway over the last week. In Norway, the inflow and reservoir data is published every Wednesday and covers 97.1 percent of the total reservoir capacity in the country. The inflow and reservoir data is transformed to percentage deviation from the median inflow or reservoir filling the current week.

Temperature data were provided by eKlima.no, an online database provided by the Norwegian Meteorological Institute. The US Energy Information Administration provided data on heating oil traded at the New York stock exchange. Natural gas price data were also provided by Nord Pool, while the European Energy Exchange (EEX) provided price data for coal. The price data for natural gas started in 2005, while the coal data starts in 2006. We have looked at prices the last trading day at the week. We have inflow and reservoir content data for all countries in the period, except for Finland in the year of 2000.

Currency exchange rates were provided by the Central Bank of Norway. Inflation (KPI-JE), industrial production volume, real GDP (not seasonally adjusted), and economic cycle data were provided by Statistics Norway. Inflation and real GDP were interpolated down to weekly numbers. The base year for KPI-JE is 1998.

Lastly the Norwegian Competition Authority provided average end-user prices for residential electricity consumers. These prices include value-added tax for all counties except Finnmark (where the value-added tax is not applicable. Transmission tariffs and electricity consumption tax are not included in these prices and may differ between regions.

3.4. Estimation framework

In the analysis, I estimate a demand equation for electricity combining instrumental variable regression methods and autoregressive distributed lag models. This section will first explain my approach in the context of the Norwegian market for electricity. The final model specification will rely on the use of automatic model selection software and how this works is therefore also explained.

3.4.2. Instrumental variable regression

According to economic theory, the price of electricity will influence the demand for electricity. Similarly, the demand for electricity will influence the price of electricity. An ordinary least square regression of consumption on price will therefore provide biased results due to this simultaneous causality. Using the identified supply side variables above I may identify how the supply side effects the price. Hence, we can (in theory) observe how consumers react to different prices holding everything else constant. This section will briefly present the theory of instrumental variables and the requirements for valid instruments. The definition of exogenous variables will also be discussed in context of the variables I will use.

Let me provide an example relevant to a hydropower dominated electricity market. Unexpectedly little inflow of water to the reservoirs may increase the opportunity cost (and thus the marginal cost) of hydropower production. The inflow to reservoirs is however not likely to have any influence on electricity demand. Say that the inflow is unexpectedly low over a sufficient period of time. Profit maximizing producers will due to higher marginal costs reduce their production. Because the market has to stay in equilibrium consumption must also decrease. Given that all other factors remain constant, the only factor that can cause reduced consumption is an increase in the price of electricity. Instrumental variable regression exploits information about price determining variables to find an unbiased estimate of price on consumption. The next following sections will describe the method in more formal details.

Phillip Wright (1861-1934) showed how a regression of quantity on price will not, estimate a demand curve, but instead estimate a combination of the supply and demand curves (Stock and Trebbi 2003). Say that one estimate a consumption function of the form:

$$C_t = \beta_0 + \alpha_1 P_t + \sum_{i=1}^K \beta_i X_{i,t} + u_t \quad (1)$$

where C_t is the consumption of electricity in period t , P_t is the price of electricity in period t , $X_{i,t}$ is an exogenous explanatory variable in period t , and u_t is the error term in period t . K denotes the number of explanatory variables (other than price). Estimating this function by OLS will not yield consistent estimates of the parameter α_1 in particular. This follows from economic theory and is due to the interaction between supply and demand: the regressor of price is correlated with the disturbance term u_t . Fitting a line through observed points of quantity and price will estimate neither a demand curve, nor a supply curve, because the points have been determined by changes in both demand and supply. Theoretically, this can be easily verified by defining a simple supply equation, where I have omitted dynamics for simplicity:

$$C_t = \gamma_0 + \gamma_1 P_t + \sum g_n Z_n + \varepsilon_t \quad (2)$$

The z variables are exogenous variables that affect supply, but not demand. Hence, both equations are identified. From the reduced form of this two equation system it is seen that P in (1) is correlated with the disturbance term u_t . This is true in even if the coefficients for the exogenous variables in (2) are equal to one, which is the case of inelastic supply.

The correlation between price P_t and the disturbance term, u_t , may be easily seen by imagining a situation where the disturbance term, u_t , in the first equation above is positive. A positive u_t increases C_t . However, an increase in C_t affect the price through equation (2). Assuming that γ_1 is positive, an increasing in C_t will lead to a decrease in P_t . Thus, if γ_1 is positive the u_t and the C_t will be positively correlated. This is a violation of the least squares assumptions and an OLS regression will therefore produce inconsistent results.

Instrumental variables estimation uses an additional, “instrumental”, variable Z to isolate the part of the price that is uncorrelated with the error term u_i . An equation for the price of electricity could be of the form:

$$P_t = a_0 + \sum_{n=1}^J \alpha_n Z_{n,t} + \varepsilon_t \quad (3)$$

In equation (3), the price of electricity, P_t , is a function of exogenous supply side variables ($Z_{1,t}, \dots, Z_{n,t}$). Some potential variables, such as deviations from median inflow to reservoirs, the price of coal, etc. were discussed as potential candidates in section 3.1.2. By estimating a price equation like (3) first, we may identify how supply side variables influence the price of electricity. These may then be used as instruments in a instrumental variable estimation. In formal terms, the instrumental variable estimation split the price variable into two components: one part that may be correlated with the regression disturbance term u_i , and another component that is uncorrelated with the disturbance term u_i . The second stage uses the uncorrelated variable to estimate the demand side price coefficient α_1 .

For α_1 to be unbiased, the instrumental variables have to satisfy two conditions: They must be relevant, $\text{corr}(Z_{i,t}, P_t) \neq 0$, and exogenous, $\text{corr}(Z_{i,t}, u_t) = 0$, where P_t is the price in period t , Z_i is the instrument in period i , and u_t is the error term in the demand equation in period t . The exogeneity was the premise for classification of instrumental variables in section 3.1.2. The relevance will be considered in the actual estimation process.

Exogenous explanatory variables are also necessary inputs in the demand equation. This is variables that are only directly affecting the demand side directly. Potential variables in this category could be percentage deviations from median temperature, changes in real gross domestic product, changes in the price of substitutes such as heating oil, etc. These variables should be uncorrelated with the error term u_t .

So far we have considered the price of electricity as an endogenous variable. Other potential endogenous variables may be the price of natural gas and carbon emission allowances. These variables may both influence demand and supply. I will discuss these in chapter 5.

The model is theoretically valid if it fulfills the four least squares assumptions, as well as the two conditions for valid instruments mentioned above. But without considering the dynamics of the market we may overlook important information. One week of low inflow may i.e. have little impact on the price of electricity as there is reservoir capacity. Twelve consecutive weeks of low inflow is however likely to cause significantly higher prices due to higher opportunity costs of water. The next section will present a widely used method to model these kinds of relationships.

3.4.3. Autoregressive distributed lag models

The last section described a method for going around the problems of correlation between the price and the disturbance term u_i in a demand function for a single period. This section will go into detail on the dynamics of demand adjustment. If the future is like the past one can forecast the future using historical relationships. To extract dynamics I therefore specify an autoregressive distributed lag model. In this model, the consumption of electricity, C_t , is specified as a function of current and lagged values of exogenous variables (such as temperature, gross domestic product, etc.) and lagged values of consumption itself. This section will briefly present the theory behind this model and explain why it is well suited for the purpose of our analysis. We further introduce the concept of stationarity. Lastly we relate the model to instrumental variable regression. The exact specification of our model will be done in later sections.

Because dynamic effects by definition occur over time, the econometric model used to estimate these dynamic effects must include lags. Otherwise, autocorrelation between different periods of time will make the results biased. Specifically, C_t can be expressed as autoregressive distributed lag of current and past values of X_t and past values of itself:

$$C_t = \delta_0 + \sum_{j=0}^K \alpha_j P_{t-j} + \sum_{i=1}^L \sum_{j=0}^N \beta_{i,j} X_{i,t-j} + \sum_{j=1}^M \gamma_j C_{t-j} + u_t \quad (4)$$

In this equation K , N and M symbolize lag lengths. The coefficient $\beta_{i,j}$ is the effect this period of a unit change in the exogenous explanatory variable $X_{i,t-j}$, j periods back. The coefficients for the past values of consumption (C_{t-1} , C_{t-2} , etc.) represent habits or preferences for consumption smoothing. This effect could be interpreted economically as behavioral or technological assumptions: A rise in the consumption level is likely sustained in future periods.

A time series like C_t is stationary if its probability distribution does not change over time. That is, if the joint distribution of $(C_{t-1}, C_{t-2}, \dots, C_{t-M})$ does not depend on time; otherwise, C_t is said to be nonstationary. In casual terms one may say that if the future is like the past one can forecast the future by looking at the past. Significant changes in the market for electricity, as well as trends in the market, may however cause our time series to be nonstationary. To avoid this we transformed several of the variables in our dataset (see the ‘potential data variables’ section). For example, notice how we do not look at inflow to reservoirs, but deviations from median inflow. By this transformation, I exclude the seasonal trend in the inflow data. I will also do test to identify potential structural changes in the market.

To identify potential structural changes in the market, which may influence the probability distribution, I do split sample analysis and forecast tests. If the model provides statistically different results during different periods of time, something has likely changed the structure of the market during the period. Bad forecasting capabilities also indicate a structural change.

Since we are working with time series data we must expand the definition of exogeneity, compared to the definition commonly used in static regression models. Past and present exogeneity requires all causal effects behind a certain point, r , in time to be zero. Mathematically, that $E(u_t | X_t, X_{t-1}, \dots, X_{t-r}) = 0$. Weather variables, such as rainfall and temperatures, can be thought of as exogenous, because they are not affected by electricity production, demand or prices.

The linear dynamic model can be estimated with instrumental variable methods. There should be no correlation between the error term and the endogenous and exogenous variables for all time periods. Furthermore, if the random variables have stationary distributions, the endogenous and exogenous variables should become independent over time. If this is satisfied, our calculations will yield consistent estimators.

By implementing the instrumental variable regression into an autoregressive distributed lag model, I have a framework to model electricity demand. The next sections will therefore specify our first model and do the estimation. But first I will explain the method of general-to-specific modeling.

3.4.4. Automatic model selection

I will use Autometrics to aid the search of models that contain the most informational variables and lag lengths. Autometrics is a computer implementation of general-to-specific modeling (see Doornik and Hendry (2009) for details). I will provide Autometrics with a model formulated large model. This model is called the general unrestricted model (GUM). It will be well specified in accordance with what we know about the market for electricity and economic theory. But it will be very general with several variables and long lag lengths. Autometrics will then reduce the model following the significance level of the regressor. Regressors with low significance level will be removed.

Our chosen significance level is 1 percent. This is then the criteria for removing regressors. It also specifies the extent to which we accept quality reductions of information: no joint reduction is allowed to be significant at 1 percent or less. If the GUM satisfies the default set of diagnostic tests, each reduction will also pass the test. Doornik and Hendry (2009) provide a detailed overview of the process.

4. The Model

I will build an autoregressive distributed lag model where several variables have been transformed to a logarithmic scale. This section first briefly discusses the reasons for using a logarithmic form. Then I will describe the general unrestricted model (GUM). The modeling is done in three stages: First, I regress the price of electricity on supply side exogenous variables using OLS to find strong instrumental variables. Second, I regress consumption on explanatory exogenous variables and the price of electricity to find important explanatory variables. In the third stage I combine the results from the first stages: the price of electricity is set endogenous and I use the variables identified in the first stage as instruments to estimate it. I then search for large outliers. I do this to identify weeks not representative to the market in general. Because the sample period is weekly data ten years back, it is necessary to implement many explanatory variables with long lags. Although this makes the model complex, the model specification (described in section 4.2) makes the important results easily identifiable.

4.1. Modeling demand elasticities

Madlener (1996) discusses different models used for modeling demand elasticities. He gives several arguments for the popularity of log-linear models. In a log-linear functional form the elasticities are directly estimated as parameters in the model. This is practical when interpreting the results. Some also argues that it is more likely that the relationship is linear if the variables are first log-transformed and then placed side by side in a model. Furthermore, conditionally normally distributed variables are preferred econometrically. Log-transformed variables are empirically distributed closer to the normal distribution than non-transformed variables. Log-transformed variables thus generally to a larger extent fit the econometric assumptions.

4.2. Model specification

I rewrite an ordinary autoregressive distributed lag (ADL) model so it is easier to identify the long run elasticities. As I argued for above, I will use a model which is linear in logs. I begin with the following model:

$$\log C_t = \delta_0 + \sum_{j=0}^K \alpha_j \log P_{t-j} + \sum_{i=1}^L \sum_{j=0}^N \beta_{i,j} \log X_{i,t-j} + \sum_{j=0}^M \gamma_j \log C_{t-j} + u_t \quad (5)$$

To estimate the long term elasticities, it is convenient to re-write the equation:

$$\log C_t = \delta_0 + \alpha_0 \Delta \log P_t + \rho \log P_{t-1} + \sum_{j=1}^{K-1} \pi_j (\Delta \log P_{t-j}) + \sum_{i=1}^L \sum_{j=0}^N \beta_{i,j} \log X_{i,t-j} + \sum_{j=0}^M \gamma_j \log C_{t-j} + u_t \quad (6)$$

where $\Delta \log(P_t) = (\log P_t - \log P_{t-1})$ and $\rho = \sum_{j=1}^K (1 + \alpha_{t-j})$. The π_j 's are linear combinations of the alphas in (5)¹⁶. The long run is a steady state situation where all variables have fully adjusted, so that $P_t = P_{t-1} = P$, $C_t = C_{t-1} = C$, and so fourth. Without new shocks there are no further changes to the variables. The long run price elasticity is equal to the coefficient of $\log(P_{t-1})$, ρ , divided by one minus the sum of the lagged consumption coefficients, $\sum_{j=0}^M \gamma_j$.

¹⁶ $\pi_{j-1} = -(\alpha_{j-2} + \alpha_{j-3} + \dots + \alpha_{j-K})$

$$\rho_{long-run} = \frac{\rho}{1 - \sum_{j=0}^M \gamma_j} \quad (7)$$

One may also transform other exogenous explanatory variables of interest. We can i.e. identify long term heating oil substitution elasticity directly by transforming the heating oil price similarly. I will do this and the results will be reported.

From the expression of $\rho_{long-run}$ we see that $-1 < \sum_{j=0}^M \gamma_j < 1$ is a necessary and sufficient condition for the existence of a globally asymptotically stable solution. In case of a stable solution, a shock has less and less influence on the solution as time passes by. If the condition is not satisfied the solution is either explosive ($\sum_{j=0}^M \gamma_j > |1|$) or unstable ($\sum_{j=0}^M \gamma_j = 1$). In the estimation process a key question in analyzing results is therefore the sum of the lagged consumption coefficients. If they in sum are equal or greater than unity in absolute terms, the long run elasticities will not approach a certain numerical value.

Having defined the functional form of our model and the methods I will use, it is time to begin the estimation process. This will be done in two stages. First relevant instruments and their time scope will be identified. Then these instruments will be used to identify significant variables in the demand function.

4.3. Finding relevant instruments

In this section I will first present how I identify relevant instruments for the price changes of electricity. The method is fairly simple and relies on the automatic model reduction software, Autometrics, discussed above. I then present the results and discuss the relevance of the variables I initially hypothesized important.

In order to identify relevant variables and lag lengths, I regress the logarithm of price changes on the potential instrument variables using an ordinary least squares equation;

$$\log(\Delta P_t) = a_0 + \sum_{i=1}^T \sum_{j=0}^K a_{i,j} \log(X_{i,t-j}) \quad (8)$$

where $X_{i,t-j}$ is potentially an instrument. Candidates, such as the deviations from median inflow to reservoirs in Norway, Sweden and Finland today and several periods back, were discussed in section 3.1.2. In the general unrestricted model, these variables are lagged 14 and 12 time periods respectively. Seasonal effects of inflow and reservoir content is measured by multiplying the inflow and reservoir variables by seasonal dummies. The start of commercial operation at the NorNed power cable is also measured by a dummy from this period. The differences in the price of coal between periods (measured on a logarithmic scale) are also potentially instruments. As described in section 2.4, coal consumption is practically irrelevant compared to the consumption of electricity. I therefore assume the coal consumption to be uncorrelated with electricity consumption (I will do test to check whether this is likely the case later). This coal price variable has 12 lags included. Autometrics then identify the relevant variables using a general-to-specific algorithm. The exact model are provided as an annex.

```

EQ( 1) Modelling DLPC by OLS
The estimation sample is: 2001(17) - 2009(50)

Coefficient Std. Error t-value t-prob Part.R^2
INO_1 -0.0150283 0.004054 -3.71 0.0002 0.0312
INO_3 -0.0190554 0.004313 -4.42 0.0000 0.0437
INO_9 0.0126769 0.003664 3.46 0.0006 0.0273
ISE_3 -0.0119003 0.004002 -2.97 0.0031 0.0203
ISE_9 -0.00502734 0.004391 -1.15 0.2528 0.0031
IFI_3 0.00419484 0.002824 1.49 0.1381 0.0051
IFI_14 0.00821416 0.003143 2.61 0.0093 0.0157
RNO_6 -0.302190 0.03919 -7.71 0.0000 0.1222
RNO_12 0.270930 0.03324 8.15 0.0000 0.1346
RSE_5 -0.151266 0.06037 -2.51 0.0126 0.0145
RSE_7 0.310432 0.06384 4.86 0.0000 0.0525
RFI_5 0.0874037 0.04819 1.81 0.0704 0.0076
RFI_7 -0.148417 0.04790 -3.10 0.0021 0.0220
INOSu_1 0.0235515 0.006214 3.79 0.0002 0.0326
INOSu_3 0.00829641 0.005925 1.40 0.1622 0.0046
INOSu_6 0.0154934 0.005048 3.07 0.0023 0.0216
ISEsp_1 -0.0214662 0.01105 -1.94 0.0528 0.0088
RNOSp_1 0.213158 0.08225 2.59 0.0099 0.0155
RSEsp_1 -0.214252 0.07836 -2.73 0.0065 0.0172
RSEsu_1 -0.116388 0.03020 -3.85 0.0001 0.0336
DLCOAL_3 0.0693693 0.04238 1.64 0.1024 0.0062
DLCOAL_5 0.121653 0.04234 2.87 0.0043 0.0190
DLCOAL_6 0.100016 0.04217 2.37 0.0182 0.0130

sigma 0.0269095 RSS 0.309199959
log-likelihood 1000.16
no. of observations 450 no. of parameters 23
mean(DLPC) -0.000442761 se(DLPC) 0.0341844

AR 1-7 test: F(7,420) = 27.137 [0.0000]**
ARCH 1-7 test: F(7,436) = 2.6066 [0.0121]*
Normality test: Chi^2(2) = 895.01 [0.0000]**
Hetero test: F(46,403) = 1.5921 [0.0107]*
RESET23 test: F(2,425) = 24.318 [0.0000]**

```

Table 1: Identifying relevant supply side variables influencing price changes of electricity using OLS

DLPC is the difference between the current and the previous week average consumer price measured in logarithms. *INO*, *ISE* and *IFI* are inflow variables for Norway, Sweden and Finland respectively. *RNO*, *RSE* and *RFI* is the reservoir variable for the same countries. *Sp* is short term for spring, *Su* is short term for summer and *F* is short term for fall. Hence, *RNOSp* is a variable that equal *RNO* in the spring and is zero all other seasons. *DLCOAL* is the difference between the current coal price and the coal price last week. The price of coal is also measures on a logarithmic scale. The bottom section of the table shows results from several different tests. The tests first become relevant in final demand equation models using the variables here identified as instruments. I may therefore safely continue the estimation process. The different tests reported are explained and discussed in more details later. Here I am simply interested in finding variables with high correlation to the electricity price.

In general, the inflow coefficients have the expected signs. A one percent positive deviation from median inflow is associated with decreasing electricity prices. There are significantly seasonal differences in how these deviations influence the electricity price. Compared with higher inflow in the winter, higher inflow in the summer has less impact on the price of electricity. This fits well with how rational hydropower producers with reservoir capacity are expected to behave: Due to a higher price level in the winter and possibilities to refuel the reservoir in the spring and summer, profits are maximized by producing more electricity in the winter relative to producing in the spring.

The coal price is also a significant factor determining the price of electricity. This result also fits economic theory well. Higher prices of coal increase the marginal cost of electricity produced in coal fired power plants. These producers will therefore reduce their production and due to increased scarcity of electricity the prices will increase. Norway does not have coal fired thermal plants, but the Norwegian market is connected to the Danish market, where coal producers have a significant market share. By selling electricity at higher prices in Denmark, electricity supply is also reduced in Norway, and prices thus increase here as well. The lag of about three weeks is not surprising since there is costly adjust productions in thermal plant. The coal prices we measures are also based on future contracts so some lags were expected.

The NorNed power cable has not played an important role for price changes in Norway, according to this regression. This may be due to limited capacity compared to the overall market. The capacity increase in week 16 2004 did neither have a significant impact according to the model. The reason for this might be that the increase was small, that it took a longer time period before it affected the market or a combination of this.

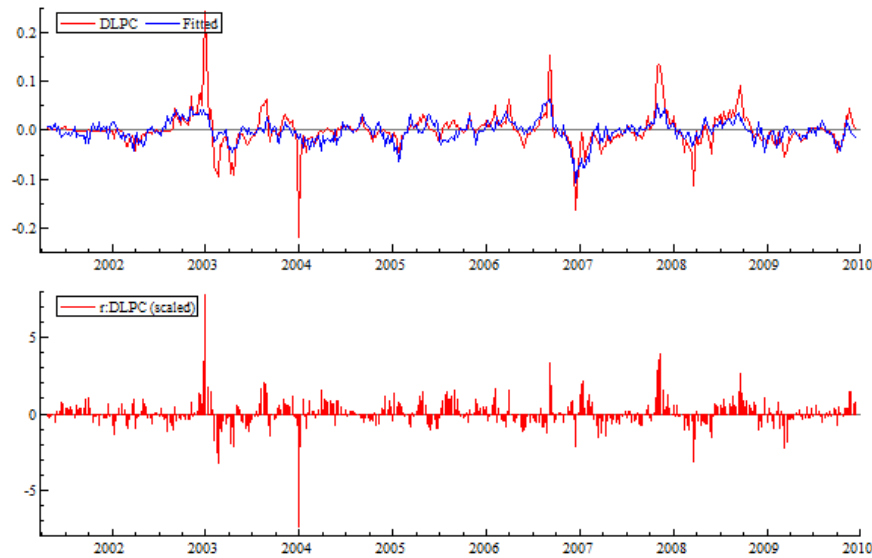


Figure 13: Actual and fitted values of DLPC using EQ1. Except for a few large outliers, the model estimates price changes quite accurately.

In figure 13, we see that the model fits the data quite well. There are two large outliers: one during the winter of 2002-2003 and one around New Year in 2004. These outliers may be related to temperatures as the winter of 2002-2003 was cold while the period around New Year in 2004 was mild. One should however be cautious in analyzing the specific coefficients of the results as this model does not contain demand side variables. Hence, it is not a surprise that all tests here reported are rejected at the five percent level.

4.4. Estimating the elasticity demand function

To estimate the elasticity demand function I follow the same procedure as I did in section 4.2: I first set up a general unrestricted model of electricity demand. This model is used to determine the relevant lag length of the prices and exogenous explanatory variables. The results from the automatic model selection are then used together with the instrumental variables to establish my first demand equation. I expand this equation by identifying large residuals to correct for non-representative weeks. This could i.e. be weeks where severe line outages are present. This section will guide the reader through the stages I here described.

Section 2.4 on consumption statistics suggested that temperatures, the price of heating oil and the aggregate economic activity level influence the demand for electricity. I include long lags to identify long term effects. There are also reasons to believe that there are seasonal patterns in electricity demand. I therefore include dummies for each month of the year. A dummy for Christmas and Easter weeks are also included. The rationale here is that businesses often severely reduce their activity level in these weeks. A price variable of electricity that equals the ordinary price of electricity from May to October, and zero otherwise is also included. This variable will capture potentially different price elasticities between seasons. Furthermore, a temperature variable which equals the ordinary temperature if spring and zero otherwise is included. A similar variable is added for the summer and fall. Because our temperature variable measure deviations from median temperatures, these variables will capture seasonal effects of temperature deviations. The rationale is that a one percent deviation may matter less in the summer than in the winter. In regards to lag length, there are few reasons to believe that temperature deviations weeks ago matter this week. The temperature variables are therefore maximally lagged two weeks.

Lastly I search for large residuals to identify outliers. Outliers in the Norwegian market could be breakdown of Swedish nuclear reactors and line outages between Norway and other major markets. Since other Nord Pool countries, such as Denmark, are connected with countries outside the Nord Pool area, demand or supply shocks in these markets may also influence the price of electricity in Norway. Demand side shocks may also cause price

variations my data can't explain. An example could be the opening of the gas processing center at Melkøya¹⁷, which require massive amounts of electricity. By not ignoring significant shocks that my original data can't explain, the results will represent behavior more accurately.

4.5. The first model

Due to the use of weekly data this is a big model with 67 explanatory variables. Table 2 reports all results for the reader's reference, while table 3 presents the interesting long term results. I will also focus on important coefficients and other results of interest in the text. The model looks reasonably good: All tests are passed and the results are not too different from those of other studies. But the split sample analysis in section 4.6 suggests a structural change of the market in the second half of 2008. In section 4.7, where I build a new model that takes the financial crisis into account. This model performs better in forecast tests and split sample analysis.

LC is the consumption of electricity on a logarithmic scale. *DLPC* is the change in the price of electricity from the current to the previous period measured on a logarithmic scale. *DLPCS* is equal *DLPC* in summer months otherwise zero. Hence, the sum of the coefficients of *DLPC* and *DLPCS* equals the percentage change in consumption of a one percentage increase in the price of electricity. The long-run solution to *LPC* equals the long-run winter season price elasticity. The long-run solution to *LPC* plus *LPCS* equals the long-run summer price elasticity

LOH is the price of heating oil on a logarithmic scale. *DLOH* is the change in the price of heating oil from period to period. The long-run solution to *LOH* is the substitution elasticity between electricity and heating oil. *TeNO* is the deviation from the median temperature the current week, measured in degrees Celsius. *LGDP* is the GDP level measured in real levels on a logarithmic scale. *DLGDP* is the change in GDP from period to period. *Mar* is a dummy that equals 1 if the current week is in March. *HOLI* is a dummy which equals one if the current week is an Easter or Christmas week. Hence, *HOLI_1* is the week before Easter as well as week 51. Weekly dummies are also reported. "*I:2003(16)*", is a dummy equal to one at week 16 of 2003.

¹⁷ Statoil (2010): "Snøhvit – Unlocking resources in the frozen North", <http://www.statoil.com/en/OurOperations/ExplorationProd/ncs/Pages/SnohvitNewEnergyHistoryInTheNorth.aspx>, accessed 10.03.2010

EQ(5) Modelling LC by IVE
The estimation sample is: 2001(15) - 2009(39)

	Coefficient	Std. Error	t-value	t-prob				
DLPC	-0.0247349	0.06307	-0.392	0.6951				
DLPCS	0.0272017	0.02449	1.11	0.2673				
LC_1	0.613496	0.04044	15.2	0.0000				
LC_2	0.191351	0.03694	5.18	0.0000				
LC_4	0.0508563	0.02324	2.19	0.0293				
LC_9	-0.0621585	0.01747	-3.56	0.0004				
DLPC_7	0.0999562	0.03626	2.76	0.0061				
DLPC_27	-0.103624	0.04090	-2.53	0.0117				
DLPC_28	0.0770389	0.04112	1.87	0.0618				
DLPC_36	0.123021	0.04088	3.01	0.0028				
DLPC_37	-0.123980	0.04135	-3.00	0.0029				
DLPC_49	-0.0739478	0.04082	-1.81	0.0708				
DLPC_50	0.126768	0.04090	3.10	0.0021				
DLPCS_2	-0.0114485	0.004630	-2.47	0.0139				
DLPCS_5	0.00989993	0.004431	2.23	0.0261				
DLPCS_12	-0.0111650	0.004150	-2.69	0.0075				
DLPCS_14	-0.00836665	0.004353	-1.92	0.0554				
DLPCS_15	-0.0213602	0.004697	-4.55	0.0000				
DLPCS_16	-0.0136792	0.004555	-3.00	0.0028				
DLPCS_20	0.00988897	0.004374	2.26	0.0244				
DLPCS_25	0.0186978	0.005008	3.73	0.0002				
DLPCS_49	-0.0192556	0.004906	-3.92	0.0001				
DLPCS_50	-0.0178343	0.004806	-3.71	0.0002				
LPC_1	-0.0208181	0.01259	-1.65	0.0991				
LPCS_1	0.0156770	0.01941	0.808	0.4198				
LOHS_1	0.000806417	0.005668	0.142	0.8869				
LGDP_1	0.242174	0.03733	6.49	0.0000				
TENO	-0.00967353	0.0008377	-11.5	0.0000				
TENO_1	0.00642711	0.0007095	9.06	0.0000				
TENOF	-0.00925569	0.001457	-6.35	0.0000				
TENOF_2	0.00623456	0.001355	4.60	0.0000				
TENOW	-0.00407331	0.001061	-3.84	0.0001				
TENOW_2	0.00520885	0.0009327	5.58	0.0000				
TENOSP	-0.00797417	0.001332	-5.99	0.0000				
TENOSP_2	0.00636741	0.001237	5.15	0.0000				
DLGDP	1.54842	0.5154	3.00	0.0028				
DLGDP_16	3.10654	0.6817	4.56	0.0000				
DLGDP_19	-3.51687	0.6620	-5.31	0.0000				
DLGDP_21	2.02301	0.6755	2.99	0.0029				
DLGDP_27	2.88227	1.050	2.74	0.0064				
DLGDP_28	-3.22638	1.053	-3.06	0.0024				
DLGDP_29	2.48745	0.9026	2.76	0.0061				
DLGDP_31	-1.70768	0.6264	-2.73	0.0067				
DLGDP_40	4.55338	1.266	3.60	0.0004				
DLGDP_41	-3.09822	1.002	-3.09	0.0021				
DLGDP_48	-1.70200	0.5841	-2.91	0.0038				
DLGDP_50	2.81437	0.7490	3.76	0.0002				
DLGDP_51	-2.57651	0.8194	-3.14	0.0018				
DLGDP_53	2.62786	0.8017	3.28	0.0011				
DLOH_18	-0.0445640	0.01667	-2.67	0.0079				
DLOH_20	0.0422556	0.01649	2.56	0.0108				
DLOH_27	0.0673203	0.01717	3.92	0.0001				
DLOH_37	-0.0307073	0.01668	-1.84	0.0665				
Apr	-0.0714568	0.02911	-2.45	0.0146				
May	-0.0893586	0.03207	-2.79	0.0056				
Jun	-0.0898408	0.03426	-2.62	0.0091				
Jul	-0.108381	0.03617	-3.00	0.0029				
Aug	-0.0719958	0.03674	-1.96	0.0508				
Sept	-0.0688645	0.03436	-2.00	0.0457				
Oct	-0.0387211	0.03096	-1.25	0.2118				
HOLI	-0.0545343	0.005981	-9.12	0.0000				
HOLI_1	0.0245277	0.006923	3.54	0.0004				
Trend	-0.000148932	2.591e-005	-5.75	0.0000				
I:2003(16)	-0.0262409	0.02191	-1.20	0.2317				
I:2004(1)	-0.0397537	0.02409	-1.65	0.0997				
I:2009(3)	0.0821501	0.02009	4.09	0.0001				
I:2006(37)	0.0407241	0.02077	1.96	0.0507				
sigma	0.0187661	RSS		0.131709887				
Reduced-form sigma	0.018972							
no. endogenous variables	3	no. of instruments		88				
no. of observations	441	no. of parameters		67				
mean(LC)	14.6137	se(LC)		0.201583				
Additional instruments:								
[0]	= INO_1							
[1]	= INO_3							
[2]	= INO_9							
[3]	= ISE_3							
[4]	= ISE_9							
[5]	= IFI_3							
[6]	= IFI_14							
[7]	= RNO_6							
[8]	= RNO_12							
[9]	= RSE_5							
[10]	= RSE_7							
[11]	= RFI_5							
[12]	= RFI_7							
[13]	= INOSu_1							
[14]	= INOSu_3							
[15]	= INOSu_6							
[16]	= ISEsp_1							
[17]	= RNOSP_1							
[18]	= RSEsp_1							
[19]	= RSEsu_1							
[20]	= DLCOAL_3							
[21]	= DLCOAL_5							
[22]	= DLCOAL_6							
Specification test: Chi^2(21) = 24.343 [0.2768]								
Testing beta = 0: Chi^2(66) = 50389. [0.0000]**								
AR 1-7 test: F(7,367) = 1.6872 [0.1107]								
ARCH 1-7 test: F(7,427) = 0.39904 [0.9028]								
Normality test: Chi^2(2) = 1.1596 [0.5600]								
Hetero test: F(117,319) = 0.91513 [0.7095]								

Table 2: Demand for electricity as a function of explanatory variables and prices. The price is estimated using the instruments reported in table 1.

The sum of the lagged demand coefficients are between zero and one. The model thus has a stable long-run solution. We see that the coefficients of changing prices in the current period (*DLPC* and *DLPCS*) are not statistically different from zero: A price hike does not necessarily cause a reduction in the use of electricity in the short run. This may explain why we have seen dramatic price peaks and volatility in the electricity price in certain periods. Long price variable lags are included. This is a sign that consumers consider prices over a considerably long time period when they determine their behavior related to energy. The short term effect of increased GDP is positive in the short run. A greater activity level in the economy creates greater need for electricity. There is furthermore a significant lag in how demand react to rising heating oil prices (there are long lags in the heating oil variable *DLOH*). The temperature, the month of year and the holiday variables (dummy for Christmas and Easter weeks) do explain a lot of the observed variation in electricity consumption, even from week to week.

Solved static long-run equation for LC [EQ(12)]

	Coefficient	Std.Error	t-value	t-prob
LPC	-0.100836	0.05440	-1.85	0.0645
LPCS	0.0759339	0.08872	0.856	0.3926
LOH	0.0039060	0.02736	0.143	0.8866
Long-run sigma = 0.0908966				

Table 3: The static long-run solution of the model in table 2.

In table 3, we see that the long-run price coefficients are small relative to the different price variables and generally expected. Long term price and substitution elasticities are small. The price elasticity is -0.10 during the winter and approximately -0.025 percent during summer. But neither price elasticities nor substitution elasticities are significant at the 5 percent level. There is thus not statistical evidence to conclude that there is a substitution effect between electricity and heating oil. There is neither statistical evidence to support the hypothesis of Bye and Hansen, of seasonal differences in the price elasticity (which they indeed find support for in their model).

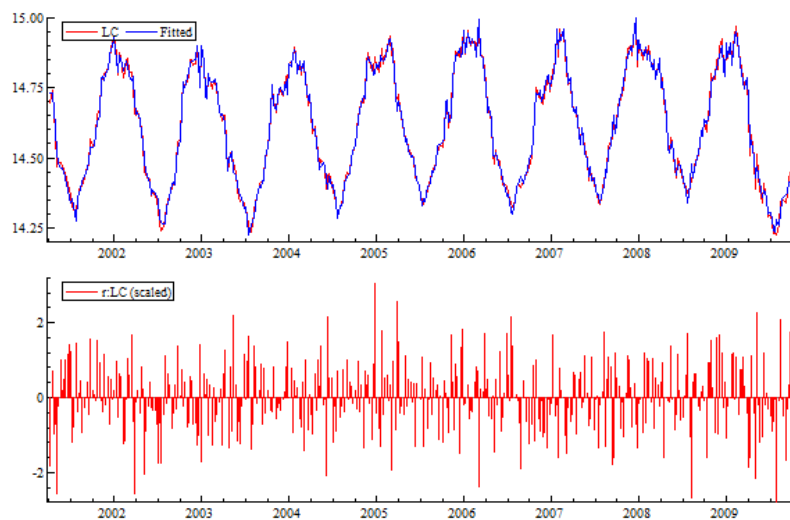


Figure 144: Actual and fitted values of electricity demand and residuals of model 1.

These results differ from the results of Bye and Hansen (2008) and Johnsen (2001). Bye and respectively estimated the long-term price elasticity in the winter to be -0.02 in the winter and 0 in the summer). My model thus indicates greater price elasticity in both seasons. This may be due to specification errors in both or one of the models, that we study different time periods studied or due to the time scope before the long run solution is reached. Bye and Hansen's sample periods is about half of mine (01.01.2000-31.12.2004), but they use hourly data. They therefore have more observations than I do. Their long-term solution is reached after about six months. Johnsen (2001) estimates the price elasticity in the interval 0.05 to 0.35. The elasticity is the highest

when the price is high (which is in the winter). Note that his study is based on data from 1994-1996. The price levels were thus low (the maximum day-ahead price during the estimation period were 0.23 NOK/kWh¹⁸) and the data are old. The high price elasticity may be explained by lower prices of substitutes. But Johnsen does not correct for price of substitutes like heating oil in his study. My estimated elasticities are however within the range of his results. The summer elasticity is probably more inelastic. This may be explained by more use of computers and other technical equipment. His winter elasticity is higher. This may be explained by more expensive substitutes and greater income levels during the sample period I study.

The specification, $\chi^2(39)$, test is an over-identifying restriction test¹⁹. The software regresses the estimated consumption function error term u_t on the instrument and control variables. If the instruments are uncorrelated with the disturbance term, their coefficients should be zero. The test tests this hypothesis. The coefficients of my instruments are thus not significantly different from zero. The p-value of the test is above 25 percent. The test therefore suggests that the instruments are exogenous.

The $\chi^2(51)$ testing coefficients equal to zero is the analogue of the OLS F-test of the R^2 equal to zero. This test is rejected at the 0.01 percent significance level. My variables are thus significant in explaining the electricity consumption.

The Anderson-Rubin test (AR 1-7 test) passes the 10 percent significance level. The test is used to indicate autocorrelation in the error term u_t which is a violation of the independence from period to period regression assumption. Potential sources for the autocorrelation could be incorrect functional form of the model, inappropriate time periods, incorrect dynamic structure, etc. Provided that no other classical assumptions are simultaneously violated the estimates are however still unbiased. The variance of the coefficients will however be affected. The standard errors of the coefficients are consequently affected.

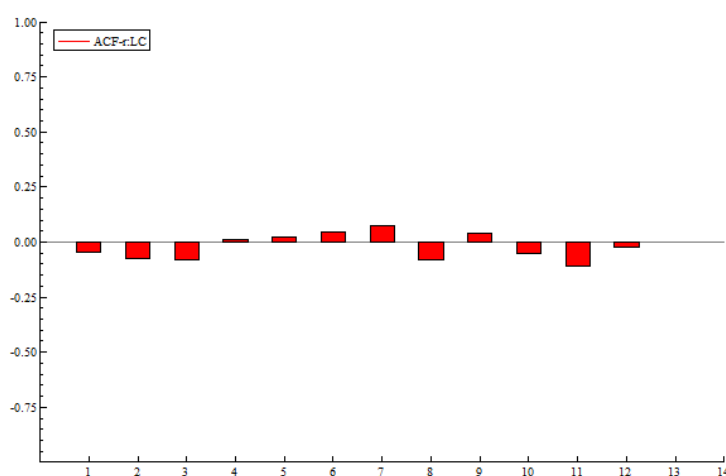


Figure 15: Autocorrelation of the residuals

The autocorrelation of the disturbance term is plotted in figure 15. We see that there is no clear pattern of positive autocorrelation. Positive autocorrelation will overestimate the standard errors and the t-values will be biased upwards. The variance of the error term will also overestimate the positive autocorrelation and exaggerate the fit of the model. A p-value of 11 percent is furthermore not uncommon for models similar to the one I have estimated. This suggests that the significance levels are unreasonably inaccurate.

The ARCH 1-7, normality and heteroskedacity tests are furthermore all passed with p-values between 55 and 90 percent. This suggests that issues such as heteroskedacity or normality are not a concern to my results.

¹⁸ This is a nominal price. It was observed in the fall of 1994.

¹⁹ See 17.3.3 in Doornik and Hendry (2009)

4.6. Forecast tests and split sample analysis

Structural changes in the market for electricity may bias the results. New technology may i.e. have changed the demand function. If so, my demand coefficients are an average of the coefficients in these different demand functions, and therefore not necessarily correct. In this section I will do split sample analysis and forecast test. If variable coefficients change significantly between sub-samples, this causes a concern of structural change in the market.

The specification test is rejected at the 5 percent level when the sample period is reduced by 1.5 years: It cannot be rejected that the instruments play a role in determining the regression error terms. The reduced significance level is likely due to the shorter sample length. With a shorter sample period the model gets less support from data. Note i.e. that the coal data first begins in the middle of 2006. The other tests are passed by large margins. The rejection of the specification test may be an indication of a structural change in the market. As it was not rejected earlier, the market participants might have changed their behavior.

Long run solution	2001(15)-2009(39)	2001(15)-2008(52)	2001(15)-2007(52)	2001(15)-2006(52)
LPC (Std. error)	-0.100836 (0.05440)	-0.0831402 (0.05261)	-0.146181 (0.04936)*	-0.1663 (0.05517)
LPCS (Std. error)	0.0759339 (0.08872)	0.0347182 (0.08558)	0.117925 (0.07647)	0.138808 (0.09647)
1-step forecast test (P-value)	-	98.06 [0.0000]**	173.47 [0.0000]**	243.65 [0.0000]**

Table 4: Long-run price elasticities estimated from different samples. * indicates significance at the 5 percent level, ** at the 1 percent level.

The forecast tests are rejected at the 1 percent level. The forecast test test whether the residuals are significantly different in the sub-sample period. The model is rich on details however and models demand quite well over the sample period. That the error terms are greater in the sub-sample period is therefore not my greatest concern: Although the deviations of the residuals increase, the forecast fits generally fits the data quite well. In figure 16 we see that the error terms in the sub-sample period are quite similar to the in-sample period error terms prior to the second half of 2008. This suggests that the financial crisis have played a role in the electricity market as well. Table 4 supports this hypothesis. The long run price elasticities did not statistically change by extending the sample from 2006(52) to 2007(52). The results using the full sample period are however quite different from the results of the pre- 2008 results.

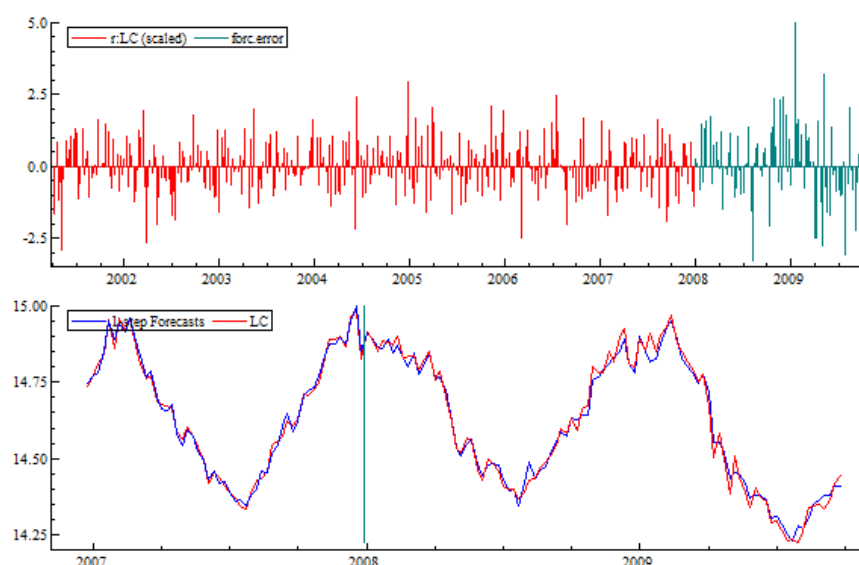


Figure 15: Forecasting 2008 and 2009 based on the sample period prior to 2009.

Industrial sectors were hit hard during the financial crisis. These sectors are often energy intensive and their reduced production may not sufficiently have been controlled for by the interpolated gross domestic product variable. Reduced electricity consumption was due to reduced demand for their output products, not changing electricity prices. The financial crisis also brought uncertainty regarding the labor market and interest rates. Decreasing consumer spending may have decreased gross domestic product, while the demand for electricity remained higher than otherwise normal. The coefficient of real GDP changes may thus have been different during the financial crisis. A dummy variable equal to one during the financial crisis may extract effects such as those discussed here.

4.7. The second model

The previous section suggested that the financial crisis may have affected the demand for electricity. This may cause inconsistent results because the demand function was different in this period compared to periods of ordinary market conditions. In this section I review a model where a dummy is included to the second regression. Except for this dummy the model is similar to the first model. This dummy equals one from September 2008 and throughout March 2009. These were the months with the greatest turmoil, uncertainty and capital losses.

Solved static long-run equation for LC				
	Coefficient	Std.Error	t-value	t-prob
LPC	-0.129395	0.04676	-2.77	0.0059
LPCS	0.119814	0.07582	1.58	0.1148
LOH	0.0422799	0.02973	1.42	0.1557

Long-run sigma = 0.0799239

Table 5: Long-run results from the second model

Specification test: $\chi^2(21) = 19.825$ [0.5323]
Testing beta = 0: $\chi^2(69) = 51294$. [0.0000]**

AR 1-7 test: $F(7,364) = 1.5908$ [0.1367]
ARCH 1-7 test: $F(7,427) = 0.45280$ [0.8682]
Normality test: $\chi^2(2) = 1.2764$ [0.5282]
Hetero test: $F(120,316) = 0.97675$ [0.5525]

Table 6: Test results for the second model

At -0.13, the long-run price elasticity is greater and more significant than what was the case in the previous model. It is also more significant with a p-value of 0.59 percent. Furthermore, it is not statistically different from sub-sample prior to 2008 version of the previous model. The explanatory power of *LPCS* is also greater. The variable is close to significant at the ten percent level. The results are thus closer to the results observed by Bye and Hansen (2008), who estimated the price elasticity during the summer to be completely inelastic. The estimated price elasticity during the summer is -0.01. The substitution elasticity between heating oil and electricity also appears more significant. It is estimated at 0.04 but the p-value is quite high. In the long run, the financial crisis has definitely played a significant role on the electricity market. Compared to other periods with other variables at similar values, electricity consumption was 0.06 percent higher during the period. The variable is significant at the five percent level.

Table 6 reports the test results of the model. We notice that the test I were most concerned about regarding the previous model, has now improved. The specification test rejected with a p-value of 53 percent (28 percent in the previous model) and the AR 1-7 test has increased its p-value by more than 2 percentage points. The other tests still have high p-values. Long-run sigma is reduced approximately one percent. This variation of the error term is thus reduced by including the financial crisis as a dummy.

Modifying the original model by including a dummy variable for the financial crisis improves the model. I do not any longer find evidence for structural changes in the market. Forecast tests are passed and the estimated coefficients are not statistically different from earlier periods.

4.8. The third model

As earlier discussed, how often one report actual consumption will affect the incentives to adjust for short term price fluctuations. For example, the electricity price is generally lower during nights and weekends. If your bill is determined from a monthly average it does not matter whether the electricity was consumed during peak hours or not. An advanced metering and report system, reporting the actual consumption at hourly intervals, will induce short term demand incentives: One could reduce the electricity costs by moving consumption to periods with lower prices. As of January 1st 2005, all systems consuming more than 100,000 kWh of electricity were required to report their consumption hourly. In this last model, I will check whether there has been a significant change in the demand equation after the introduction of this new requirement.

Using model number two, I add a dummy equal to one from January 1st 2005 and throughout the rest of the sample period. Because the systems were required functional at this date, I include several lags to this dummy. By experimenting, I find the dummy most significant 15 weeks prior to January 1st. This variable is then the only difference between model of the last section and this section. It is estimated positive with a significance level of 1.9 percent.

	Solved static long-run equation for LC			
	Coefficient	Std.Error	t-value	t-prob
LPC	-0.123498	0.04661	-2.65	0.0084
LPCS	0.106226	0.07596	1.40	0.1627
LOH	0.0486364	0.02948	1.65	0.0998
Long-run sigma = 0.0792557				

Table 7: Long-run results from the third model

Specification test: $\chi^2(21) = 20.435$ [0.4939]
 Testing beta = 0: $\chi^2(70) = 51912$ [0.0000]**

AR 1-7 test: $F(7,363) = 1.8788$ [0.0719]
 ARCH 1-7 test: $F(7,427) = 0.36316$ [0.9233]
 Normality test: $\chi^2(2) = 1.7083$ [0.4256]
 Hetero test: $F(121,315) = 0.95785$ [0.6030]

Table 8: Test results for the third model

The winter price elasticity is estimated marginally below the estimate in model 2. The price elasticity during the summer season decreases by more than 0.01 percentage points. The standard error of *LPCS* is marginally increased however. The substitution elasticity with regards to heating oil is increased, and the standard error is reduced. Although the results are not significantly different from the results of model two, model three suggests that there is greater price concerns in the period after 2005. In particular, the price elasticity during the summer has almost doubled from -0.009 to -0.017. Greater substitution elasticity also suggests that the demand is more sensitive to price movements in the latter period.

One may argue that other factors may have contributed to these changes. An example could be changes in the stock of electrical equipment. Heat pumps have i.e. become popular over the period. If these systematically replaced heating oil fired owns the demand for electricity might have increased while the demand for heating oil has decreased. I have not had the resources to investigate this issue further however. A convincing analysis in one direction regarding the policy is therefore has to investigate the issue further. Also note that the effect of hourly consumption measuring systems may also be stronger than here estimated because large consumers might have bought the system prior to 2005 for economic reasons. I find this argument unlikely however: If so, there would not have been any point in making the hourly system mandatory in the first place.

	LPC	LPCS	LOH	L-R sigma
Model 1	-0.100836	0.075934	0.0039060	0.0908966
Model 2	-0.129395	0.119814	0.0422799	0.0799239
Model 3	-0.123498	0.106226	0.0486364	0.0792557

Table 9: Comparison of central coefficients in the different models

Table 9 summarizes the important coefficients of the different models, and their long-run standard error of regression (sigma). We see that the substitution elasticity has generally increased as more variables have been included. The long-run equation standard error (sigma) also decreases.

The next section will consider how here omitted may influence the results if they were included.

5. Further discussion of validity

Although the models have about seventy explanatory variables several potentially important variables are excluded. This section will discuss the validity of my results. I will focus on internal validity and in particular omitted variable bias. The lack of reliable data at the needed frequency is the main reason for why most of the variables are not included in my models. But there are also variables in which I have data, but these data are however difficult to model. The price of natural gas and carbon dioxide emissions are i.e. often reported as important to the electricity market. I have the required data for both these variables. But their actual effects are difficult to model, because they both affect demand and supply of electricity simultaneously.

I argue that the price of carbon emission allowances are not likely to threaten the validity of my results because they this far has played a limited role in the general energy market. Their price are furthermore mostly determined by variables already important for the price of electricity – and their influence is therefore to some

extent already covered for by the other variables included in the analysis. The price of natural gas is however likely to be more important, because natural gas is an important source of energy in the Nord Pool area. I argue that other variables omitted do in general are not likely pose a threat to the validity of the model.

5.1.1. Wood

Wood is still an important source for heating in Norway. But there is little reliable data on prices. Wood may also be chopped for personal consumption without any monetary form of payment. Nesbakken (1999) set up a two-stage model where heating technology is included. The results are close to the same as in Nesbakken (1998) reported above. Because wood is not included in our model, the price elasticity may seem positively biased, since the substitution effect between wood and electricity is ignored. On the other hand, Statistics Norway estimate the consumption of wood to be relatively small compared to the consumption of electricity overall. The lack of variable related to the price of wood is therefore not likely to cause significant loss to the quality of my estimate. If there wood is an important factor, my price elasticity estimate is likely to be positively biased as the substitution from electricity to wood based heating appears to only be caused of high electricity prices.

5.1.2. Grid congestions

Grid congestions and outages may also cause prices to increase in periods. Line outages between Norway and the neighboring countries will limit supply and thus cause prices to increase. Since I do not have the resources to include this information into our model, our determination of prices may be incomplete. The same line of argument applies for technical problems and outages among electricity producers in the Nord Pool area. On the other hand, many outages are expected in the market. The effect in a specific week may therefore be limited. Line outages is however likely uncorrelated with consumption. Line outages is thus likely to be a problem in identifying supply side effects on prices, and not a cause for omitted variable bias. Significant outages or breakdowns are likely to be picked up by the large residuals identification algorithm in Autometrics as well. Bye and Hansen (2008) takes grid congestions into account.. As my results are not that different from theirs, this suggests that these variables are not that important in explaining the results.

5.1.3. Snow data

Snow data is also important for the intertemporal behavior of hydropower producers. Huge snow reservoirs in the Scandinavian mountains will cause high inflows in the spring. If this information is factored into electricity prices, the price will be lower today due to lower opportunity costs of using water. The effect of this is however likely to be limited in my model since we will see huge inflows later in the spring, of which we have data. Snow data is also likely to be uncorrelated with consumption. Snow data is thus likely to be a problem in identifying supply side effects on prices, and not a big concern as an omitted variable.

5.1.4. Stock of electrical equipment

Electricity is an indirect good and the optimal electricity consumption level therefore depends on the stock of electrical equipment. Consumers may also use several technologies for heating. Wood, and to some degree oil, fired stoves are common. Nesbakken (1998) tests the stability of a model that focuses on the relationship between the choice of heating equipment and the residential energy consumption.

I have not included any information about heating equipment in my analysis, since I assume it to be quite stable over the period. If the heating equipment were important, the split sample analysis would also have identified this. This omitted information is thus probably not a cause of concern for the validity of my results. My results are furthermore not too different from the results she reports. Nesbakken (1998) estimates the short run energy price elasticity to -0.53 in 1995. This is not too different from the winter end-price electricity elasticity I estimate if one includes grid rent and taxes.

5.1.5. *Natural gas*

Table 0 reported that 4.9 percent of the total electricity generation in the Nord Pool area was generated from natural gas in 2008. Since the late 1990s natural gas has also covered an increasing input share in central heating plants. Central heating plants have also increased in importance during this period. In 2008 gas products amounted to 8 percent of the industrial energy consumption in Norway. The price of natural gas is therefore likely to be correlated with both demand and supply directly. It is therefore an endogenous variable. Important factors influencing the price of natural gas are temperature, economic growth, as well as prices of substitutes and CO₂ allowances. There are mechanisms that make it difficult to predict the outcome of decreasing natural gas prices. Lower prices may increase demand for heating from gas, and reduce the demand for electrical heating services. On the hand, increased industrial demand may also increase the demand for electricity. For Norway, which is the third largest natural gas producer in the world, this may turn out especially important. Electricity is used in huge quantities to freeze gas for exports. It is difficult to tell in which direction the gas price influences electricity demand.

5.1.6. *Carbon dioxide emission allowances*

The carbon dioxide emission allowances prices (“CO₂ prices”) are left out of my models for two reasons. First, they are difficult to model due to simultaneous causality. Second, I already control for many of the variables important to the CO₂ emission prices.

CO₂ prices affect the demand for energy because huge consumers of electricity in Norway, such as energy installations above 20 MW and fertilizer production are included in system. Supply is also affected because coal and gas powered thermal plants must buy allowances equal to the amount of CO₂ they emit. Increased prices of CO₂ emission allowances may therefore i) reduce the demand for electricity ii) reduce the supply of electricity. The effect on the electricity price depends on which effect that is the stronger.

Benz and Trück (2009) analyze the price of CO₂ emissions. They argue that variables such as temperature, rain fall and wind speed, as well as fuel prices and economic growth influences the price of CO₂ allowances. The price difference between gas and coal is also important, since there is considerable capacity for switching from coal to natural gas and other CO₂-free fuels in several states, especially Germany and Spain. Notice that these are much the same variables important to the price of electricity.

In the current carbon dioxide emission allowance regime, I therefore find it most practical to leave the price of CO₂ out of the model. After 2012, when the carbon market is expanded to include more sectors, this should be reconsidered.

6. **Conclusion**

The thesis has analyzed the demand for electric power using weekly data from the period 2000-2010. The main focus has been to estimate how the price of electricity and heating oil affects aggregate demand. I find that total electricity demand do respond negatively to rising prices of electricity and positively to increasing heating oil prices. Like existing studies I find the price elasticity to be close to inelastic during the summer. This may be explained by the mild Norwegian summer where most electricity is consumed for technical equipment. The long-run price elasticity is estimated at -0.13 in the winter and -0.02 during the summer. But the effects are small and uncertain in the shorter run. Inelastic short-run demand may have contributed to the extreme price peaks we have seen during the period, such as the winter of 2002-03. This suggests that greater transmission capacity could reduce the price volatility of electricity during periods with huge consumption.

I find evidence of a structural change in the market at the end of 2004. The timing and the effect on the market correspond well to a regulatory change: On January 1st 2005, hourly consumption reporting became mandatory to electrical systems consuming more than 100,000 kWh annually. This increased their incentives for utilizing

short term price fluctuations. In the data we find evidence of this. The substitution effect towards heating oil is stronger in the models that are taking this policy change into account. Summer demand also becomes more elastic.

The demand is different during the financial crisis of 2008-2009 and stabilizes thereafter. I do not find further evidence for structural changes in the market. This suggests that the model replicates the market quite accurately and that the market has remained relatively stable over the sample period. The model could be useful for forecasting demand and investment decision. One should however be aware of future regulations, such as expansions in carbon trading schemes and increased focus on mandatory hourly consumption reporting systems. One should also notice that the models generally perform worse during periods of great economic turmoil.

My elasticities are greater than what Bye and Hansen (2008) find and smaller than those estimated by Johnsen (2001). We all find the price elasticity to be the greatest during the winter season. In the summer season Johnsen estimates the price elasticity around -0.05. Bye and Hansen estimates demand to be inelastic during the summer. The differences may be due to different time periods studied and the functional form of the models. My study does however control for more variables and it covers a greater time period. That I control for substitution towards heating oil may i.e. cause my price elasticities to be lower than theirs. This suggests that my results are representative.

The analysis may be expanded to account for weaknesses. Further analyses could adjust for regional price differences in electricity prices and grid rents. It could then be possible to compare different entities over time. One could also take the distribution of contract types into account, i.e. how many percent of the consumers that were on spot price contracts. Furthermore, one could include more explanatory variables. The price of carbon dioxide emission and natural gas are obvious candidates. But wood related heating products could also be used. Carbon dioxide emission allowances and natural gas prices are difficult to model due to simultaneous causality. Quality data on the price of wood related products are hard to find, but easy to model. Micro level data on consumption could also yield an interesting alternative to the approach of this thesis.

The findings indicate that a tax on electricity is probably quite efficient because aggregate electricity demand only to a small extent reacts to prices. A tax is neither likely to switch demand in favor of substitutes such as heating oil. Assuming that the market remains relatively similar, the tax therefore creates limited distortions in the market. From an eco-political perspective, the limited response to prices further illustrates how challenging it is to decrease energy demand. End-user prices must be expected to be high for a long period of time before one can expect to see great demand adjustment.

Further analyses could adjust for regional price differences in electricity prices and grid rents. It could then be possible to compare different entities over time. One could also take the distribution of contract types into account, i.e. how many percent of the consumers that were on spot price contracts. Furthermore, one could include more explanatory variables. Micro level data on consumption also represent an interesting alternative to the approach of this thesis.

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